China's Nationwide CO_2 Emissions Trading System: A General Equilibrium Assessment

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Working Paper 24-02
February 2024

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Acknowledgments

We are grateful for helpful comments from Carolyn Fischer, Guojun He, Christopher R. Knittel, Gilbert E. Metcalf, Alistair Ritchie, Thomas Rutherford, Roberton Williams, Xiliang Zhang, and participants in the NBER Environmental and Energy Economics Program Meeting, World Bank Climate Change and Development Research Seminar, Mannheim Conference on Energy and Environment, and AERE 2023 Summer Conference. We thank Shuxiao Wang and Yisheng Sun for contributing data and outputs from their air-quality model and Shifrah Aron-Dine, Bing Liu and Eric Weiner for excellent research assistance. We also gratefully acknowledge financial support from the Energy Foundation China, Asia Society Policy Institute, National Natural Science Foundation of China, Ministry of Education of China, and Environmental Defense Fund.

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Abstract

China's recently launched CO_2 emissions trading system, already the world's largest, aims to contribute importantly to global reductions in greenhouse gas emissions. The system, a tradable performance standard (TPS), differs importantly from cap and trade (C&T), the principal approach used in other countries. We offer a dynamic general equilibrium assessment of this new venture, employing a model that uniquely considers institutional and fiscal features of China's economy that influence economy-wide policy costs and distributional impacts.

Key findings include the following. The TPS's environmental benefits exceed its costs by a factor of five when only the climate benefits are considered and by a significantly higher factor when health benefits from improved air quality are included. Its interactions with China's fiscal system substantially affect its costs relative to those of C&T. Employing a single benchmark for the electricity sector would lower costs by over a third relative to the existing four-benchmark system but increase the standard deviation of percentage income losses across provinces by more than 60 percent. Introducing an auction as a complementary source of allowance supply can lower economywide costs by at least 30 percent.

Contents

1. Introduction

China has launched an ambitious nationwide program to reduce emissions of carbon dioxide (CO_2) and address climate change. Introduced in 2021, the program has already become the world's largest emissions trading system. It is expected to make a major contribution to halting aggregate emissions growth by 2030 and achieving net-zero CO_2 emissions before 2060.

The new system is a tradable performance standard (TPS), a system in which compliance depends on a covered facility's emissions intensity. In every compliance period, the government assigns each covered facility emissions allowances based on its output and a government-assigned "benchmark" ratio of emissions per unit of output. In general, the benchmarks are set below the average initial emissions intensities across the covered facilities, which implies that China's TPS will require an overall reduction in the emissions-output ratio.

A TPS is an example of an output-oriented emissions intensity standard, as it imposes a ceiling on the ratio of emissions to output.[1] It can be contrasted with an input-oriented rate-based standard, which imposes a floor on the ratio of "clean" (low-polluting) to "dirty" (high-polluting) inputs to production.[2] A TPS includes provisions for trading emissions allowances. Trades alter the distribution of abatement efforts across facilities and bring about more abatement by facilities that can achieve emissions reductions at the lowest cost. In this respect, a TPS shares a key feature of cap and trade (C&T), the principal type of emissions trading program used in other countries.

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[1] Fischer (2001) offered a foundational theoretical study of the efficiency properties of a TPS. Subsequent studies examining potential or actual US rate-based climate policies include Fischer et al. (2017), Bushnell et al. (2017), Zhang et al. (2018), and Chen et al. (2018). Recent studies of China's TPS include Pizer and Zhang (2018), Goulder et al. (2022), Wang et al. (2022), and Karplus and Zhang (2017).

[2] Examples of input-oriented intensity standards include low-carbon fuel standards, which have been introduced in several US states, and renewable portfolio standards, which establish a floor on the ratio of renewables-generated to fossil-generated electricity purchased by electric utilities. Input-oriented intensity standards implicitly subsidize the cleaner inputs and tax the dirtier ones. Studies of low-carbon fuel standards include Holland et al. (2009, 2015), and Bento et al. (2020). Analyses of renewable portfolio standards include Fischer (2010), Fischer and Preonas (2010), and Bento et al. (2018). A close cousin to a renewable portfolio standard is a clean electricity standard, which imposes a floor on the ratio of "clean" electricity to fossil-generated electricity used by utilities, where "clean" may also include energy from nuclear power plants and renewable sources. Goulder et al. (2016) and Borenstein and Kellogg (2022) examine such standards. Fullerton and Metcalf (2001), Fischer and Newell (2008), Goulder and Parry (2008), Parry et al. (2016), Fischer et al. (2017), Metcalf (2019), and Dimanchev and Knittel (2023) survey the efficiency attractions and limitations of a wide range of climate policy instruments, including intensity standards and cap and trade.

However, a TPS differs from C&T in important ways. Under C&T, a covered facility's compliance is based on the absolute quantity of its emissions over the compliance period. This quantity must not exceed the facility's allocated emissions allowances, an amount that usually is exogenous from the covered facility's perspective.[3] In contrast, under the TPS's intensity-based approach, the number of allowances granted to a covered facility is endogenous: it is the product of the facility's assigned benchmark and its chosen level of output. This intensity-based allocation method offers the covered facility just enough allowances to justify the emissions it would generate if its actual emissions-output ratio matched its benchmark. The endogeneity of the allowance allocation is an important difference from C&T—a difference with important implications for the costs of achieving the nation's overall emission-reduction targets and the distributional impacts.

This paper presents the structure and results from a multisector, multiperiod general equilibrium model designed to evaluate China's new effort. We apply the model to assess the TPS's impact on output levels, production costs, prices, and CO2 emissions over the 2020–2035 interval.

The model has several distinguishing features that enable it to identify economic forces and outcomes that have received little prior recognition. First, it pays close attention to the structure and compliance obligations of China's TPS. Much of the earlier literature on it disregards significant differences between the TPS and C&T. Although some relatively recent studies of China's nationwide climate policy efforts recognize these differences,[4] this paper makes a further contribution by considering how institutional and regulatory features of China's economy influence TPS and C&T outcomes. These features include the administered pricing of some electricity output, supporting policies for renewable electricity, pre-existing taxes and subsidies, and the preferential treatment of state-owned enterprises (SOEs). The paper shows that these features significantly influence the TPS's costs and their differences compared to C&T.

Second, the model employs a general equilibrium framework, which enables it to address interactions among sectors covered by the TPS and between covered and uncovered sectors. Earlier studies examining China's TPS have tended to employ partial equilibrium models.[5] We are aware of only one general equilibrium model that studied China's TPS: Yu et al. (2022).[6] Our model differs from that one in several ways.

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[3] A few C&T systems include provisions for output-based allocation, which connects a facility's allowance allocation to its chosen level of output; thus, the allocation is endogenous in this case.
[4] See, for example, Geng and Fan (2021), Goulder et al. (2022), IEA and Tsinghua University (2021), Ma and Qian (2022), Wang et al. (2022), Yu et al. (2022), and Zhang et al. (2023).
[5] The partial equilibrium studies include Geng and Fan (2021), Goulder et al. (2022), IEA (2022), Ma and Qian (2022), Wang et al. (2022), and Zhang et al. (2023).
[6] Lin and Jia (2019), Jin et al. (2020), and Wu et al. (2022) assess the general equilibrium impacts of a nationwide emissions trading system in China. However, the systems considered in these studies are C&T rather than a TPS.

In addition to incorporating the institutional and regulatory features just described, it employs plant-level data, enabling it to account for heterogeneous production technologies within sectors and the within- and across-sector variation of TPS benchmarks—consistent with the actual TPS design. In addition, while Yu et al. focus only on the first TPS phase, when it covers only the electricity sector, our analysis also considers the later phases, during which coverage extends to several other sectors.

Third, the model is intertemporal, capturing changes in policy stringency and impacts over time. The few TPS studies that incorporate intertemporal dynamics tend to focus on individual sectors.[7] Our model's dynamic general equilibrium framework can assess how the absolute and relative costs of the TPS and C&T change over time with the changes in sector coverage and policy stringency.

Finally, the model has considerable flexibility in terms of the range of future TPS policy designs it can examine, dimensions that have not been comprehensively analyzed in the literature. These include alternative specifications for the variation and average stringency of benchmarks and the introduction of allowance auctioning. Although China has already introduced the first phase of the TPS, the Ministry of Environment and Ecology (MEE)—responsible for designing and implementing the program—is continuing to make important decisions about the design of later phases. The model can incorporate the alternative potential policy designs, which have differing implications for aggregate costs, their distribution across sectors and regions, and the scale of emissions reductions. The flexibility makes this model poised to offer important policy recommendations for China's continually evolving carbon emissions trading system.

The results from our analysis yield unique and significant insights into the potential impacts of China's new nationwide climate policy effort. First, we find that the TPS's environmental benefits are likely to be well above its economic cost. Our central estimate is that the climate benefits from the TPS's emissions reduction over the 2020-2035 interval would exceed its cost by a factor of more than five. Including the health benefits from improved local air quality increases the estimated benefit-cost ratio to 26.[8] These ratios apply when we employ the Biden administration's estimates of the "social cost of carbon" (SCC)—the discounted climate benefit from an

[7] See, for example, Becker (2023/) and Yu et al. (2022).

[8] The climate benefits from CO2 reductions are 6–43 trillion RMB under a plausible range of values for the SCC, model parameters, and policy stringency over the 2020–2035 interval. When health co-benefits are considered, the TPS's total environmental benefits are 19–122 trillion RMB, with 53 trillion as the central estimate. This compares with economic costs of 1–3 trillion RMB under the same range of model parameters and policy stringency (see Section 6.3).

incremental reduction in CO_2 emissions. Recent studies obtain considerably larger estimates of the SCC. Employing these estimates yields considerably higher benefit-cost ratios.[9]

Second, the planned stringency of China's TPS is less than the efficiency-maximizing level. Efficiency maximization requires that marginal abatement cost equal marginal environmental benefit. Our results indicate that over the 2020-2035 interval, the average discounted marginal cost of abatement[10] is well below the central estimates by the Biden administration of the marginal benefits from emissions abatement during this interval, as expressed by the SCC. With the Biden administration's SCC estimates, efficiency maximization would call for benchmarks that are 9 percent tighter than the current and planned benchmarks under the TPS. Using the efficiency-maximizing benchmarks would lead to emissions reductions over the interval that are twice as large as what seems likely to result from the current and projected benchmarks over this interval. Using the higher SCC estimates from recent studies would call for still greater stringency and associated emissions reductions.

Third, the relative costs of the TPS and an equivalent C&T system change significantly over time. In the early years, the TPS's costs are only slightly higher than those of an equivalently stringent C&T system, but its cost disadvantage becomes more significant over time. We identify three factors that explain this pattern, two of which have not been recognized. The factor recognized in the literature alludes to the TPS's method for allowance allocation. The TPS implicitly subsidizes intended output, as covered facilities receive free allowances for each additional unit of production. The subsidy causes covered firms to rely too little (from an efficiency point of view) on output-reduction to achieve compliance, as reducing output implies a reduced allowance allocation. This factor handicaps the TPS relative to C&T, which includes no such subsidy. This paper reveals two additional and significant determinants of the TPS's absolute and relative costs. First, the TPS's excess cost over C&T increases with the stringency of the emissions-reduction target. Increased stringency leads to higher allowance prices, which, as shown, gives greater importance to the TPS's implicit subsidy. This explains the observed growing gap over time in the TPS's aggregate abatement cost relative to the aggregate cost under C&T as stringency increases and allowance prices rise. Second, the relative costs also depend on the extent of pre-

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[9] Rennert et al. (2022) estimate the SCC (evaluated in 2020) to be 1,277 RMB (185 US dollars) per ton of CO_2; Carleton and Greenstone (2022) suggest using 863 RMB (125 US dollars) per ton of CO_2. These recent estimations are much higher than the Biden administration's central estimate of 353 RMB (51 US dollars) per ton.

[10] We obtain the economywide marginal cost by evaluating the cumulative economywide cost from an incremental tightening of benchmarks relative to their values under the TPS in the central case. Specifically, the average marginal cost per ton is the present value of cumulative change in GDP over 2020–2035 divided by the associated cumulative change in emissions relative to the baseline, using an annual discount rate of 5 percent. The economywide marginal cost of abatement is different from that of individual covered facilities (or the allowance price, under assumptions of pure competition and a perfectly functioning allowance market), as emissions reductions achieved by covered facilities affect prices and input costs to noncovered firms.

existing taxes on capital, labor, and intermediate inputs. Both the TPS and C&T give rise to higher output prices by raising private production costs. The higher output prices exacerbate the economic distortions associated with these pre-existing taxes—this is the "tax-interaction" effect that has been examined in prior theoretical and empirical literature.[11] But the TPS's implicit output subsidy leads to smaller increases in output prices than those occurring under C&T. As a result, the adverse tax-interaction effect is smaller under the TPS than under C&T. This offsets what otherwise would be a larger cost-effectiveness disadvantage. This offset is quantitatively important. In the shorter term, it eliminates almost all the gap in costs that otherwise would apply.

Fourth, supplying some allowances under the TPS via an auction can lower the economic costs of achieving given emissions-reduction targets.[12] Our central estimate is that introducing an allowance auction would lower economywide costs by 30–43 percent relative to the no-auction case, depending on how auction revenues are recycled. Introducing auctioning lowers costs for two reasons. First, because allowance allocation via auction does not involve an implicit output subsidy, the distortionary cost of the emissions trading system is lower when auctioning contributes to allowance supply. Second, revenue from the auction can be recycled in ways that lower costs further. The cost reduction is especially large when the auction revenue is used to finance cuts in pre-existing capital and labor tax rates. This lowers the distortionary effects of pre-existing labor and capital taxes on production decisions. Introducing an auction also affects the sectoral distribution of output and profit. Using auction revenue to finance subsidies for wind- and solar-generated electricity significantly increases the market penetration of renewable energy sources. And devoting the revenues to compensation to the coal and mining sectors (which otherwise would suffer the largest profit losses) can fully offset the potential adverse profit impact.

Fifth, the simulation results reveal important trade-offs between cost-effectiveness and distributional equity. Although distributional concerns can be addressed through the use of varying benchmarks, greater benchmark variation raises aggregate costs by widening the disparities in the marginal costs of production. The TPS currently in place has four different benchmarks for the electricity sector, and it is plausible that this will remain true through 2035. Employing a single benchmark over this interval would lower economywide costs by 34 percent relative to those in the four-benchmark case but increase the standard deviation of percentage income losses across provinces by more than 60 percent.

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[11] Lee and Misiolek (1986), Oates (1995), Bovenberg and Goulder (1996), Parry (1997), Goulder et al. (1997), Fullerton and Metcalf (2001), Williams (2002), and West and Williams (2007).
[12] Strictly speaking, the system is no longer a TPS once an auction is introduced, because a covered facility's compliance will no longer depend on achieving its assigned emissions–output ratio. Rather, it will require that total emissions not exceed the *level* of emissions authorized by its total allowance holdings—the sum of the allowances received free as a function of the prescribed benchmark and the allowances purchased at the auction or on the trading market.

The rest of this paper is organized as follows. Section 2 describes the basic features of the TPS and provides a simple analytical model of the incentives it yields for covered facilities' choices of inputs, levels of output, and purchases or sales of emissions allowances. Section 3 presents the numerical model's structure, and Section 4 indicates its data and parameters. Section 5 describes the policies examined, and Section 6 presents and interprets the outcomes from policy simulations. Section 7 offers conclusions.

2. The TPS

2.1. Basic Features

A TPS is a rate-based (or intensity-based) emissions trading system. As mentioned, emissions allowances are allocated to covered facilities in proportion to their levels of output. The endogeneity of the allocation is a key difference from C&T—a difference with important implications for output choices, emissions, and economywide policy costs.

China's TPS includes provisions for emissions allowance trading within and across sectors. Without trading, a performance standard would require each covered facility to achieve an emissions–output ratio not exceeding its assigned benchmark. With trading, the facility's initial allocation of allowances, plus (minus) any that it purchases (sells) on the trading market, must be sufficient to justify its emissions during the compliance period. Allowance trading can reduce aggregate costs of lowering emissions by bringing marginal abatement costs closer to equality.

The TPS will be introduced in phases. The first began in 2021 and covers only the power sector. In the second phase, likely to begin in late 2023 or early 2024, coverage will expand to include the cement and aluminum sectors and possibly the iron and steel sector.[13] At least one further phase is expected, covering additional manufacturing sectors, which are expected to be pulp and paper, other nonmetal products, other nonferrous metals, raw chemicals, and petroleum refining.

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[13] Uncertainty remains as to whether the iron and steel sector will be covered under Phase 2. This paper's simulations assume that it will.

2.2. Producer Behavior and Efficiency Implications

The following framework indicates how covered facilities minimize costs of compliance under the TPS and C&T via three channels: (a) reducing emissions intensity (emissions per unit of output), (b) reducing output supply, and (c) allowance trading. We start with a focus on the electricity sector, which faces administered prices for some of the electricity supplied.[14] We briefly discuss the framework for other sectors, which is simpler because administered prices do not apply.

We assume that firms are price takers in both the product and allowance trading markets.[15] Under the TPS, the profit function for electricity generators is[16]

$$\pi_{ELEC}^{TPS} = \overline{pq} + p(q - \overline{q}) - C(q,e) - t(e - \beta q), \tag{1}$$

where *p* denotes the market price, *q* the level of output, *C* the total cost of production, *t* the market price of carbon allowances, and β the benchmark. Generators sell a fixed amount of their electricity $\overline{q}$ at a government-administered price $\overline{p}$ and sell the electricity beyond that production level at market prices. The profit function can be rewritten as

$$\pi_{ELEC}^{TPS} = pq + (\overline{p} - p)\overline{q} - C(q,e) - t(e - \beta q). \tag{2}$$

For other sectors, outputs are sold at market prices, and thus the profit function is

$$\pi_{NON-ELEC}^{TPS} = pq - C(q,e) - t(e - \beta q) \tag{3}$$

[14] The analytical model's structure is similar to that in Goulder et al. (2022), a partial equilibrium study of the electricity sector.

[15] No evidence suggests the existence of market power in the national emissions trading system. Some studies, such as Wang et al. (2021) and Zhu et al. (2020), obtained evidence of the limited exercise of market power in the earlier regional pilot programs. We anticipate that market power will be negligible in the national market in light of the market's greater scope and much larger number of participants.

[16] The profit function could be expressed as a function of input choices denoted by a vector *x*. Expression 2 could be rewritten as $\pi_{ELEC}^{TPS} = pq(x) + (\overline{p} - p)\overline{q} - C(x) - t(e(x) - \beta q(x))$, where emissions and output levels are functions of input choices given by the vector *x*. The first-order condition with respect to x_i (with *i* indexing inputs) yields $\partial \pi^{TPS} / \partial x_i : p\partial q / \partial x_i = C_{x_i} + t(\partial e / \partial x_i - \beta \partial q / \partial x_i)$, which indicates that the marginal benefit of input x_i must equal its marginal cost. Since $\partial e / \partial x_i - \beta \partial q / \partial x_i$ on the right-hand side differs across inputs, the TPS induces input substitution. The more emissions-intensive input has a higher $\partial e / \partial x_i$ than a less emissions-intensive one. Hence the TPS causes the low-intensity input's marginal cost (left-hand side) to decline relative to that of a high-intensity input, leading firms to substitute away from the emission-intensive inputs.

βq represents allowances allocated to the facility. Facilities with relatively low initial emissions intensities—that is, below their benchmarks—will receive more allowances than what is needed for compliance. For these facilities, $t(e - \beta q)$ is negative. They have incentives to increase output,[17] as this will expand their allowance allocation, giving them additional allowances to sell.

In contrast, facilities with relatively high initial emissions intensities will be above the levels of their allowances, rendering $t(e - \beta q)$ positive. Such facilities can reduce the costs of allowance purchases $t(e - \beta q)$ by reducing output. Because that diminishes the allowance allocation, the firm faces an implicit tax on the output reduction. As a result, under the TPS the high-intensity facilities tend to exploit output reduction less than under an equivalent C&T system. Correspondingly, to achieve compliance, these must rely relatively more on reductions in input intensity of production. The numerical results reveal large differences between the TPS and C&T in terms of their relative reliance on output reduction and on reduced input intensities.

For both electricity and nonelectricity firms, the first-order conditions for the two decision variables *e* and *q* are

$$\partial \pi^{TPS} / \partial e: \ -C_e = t \tag{4}$$

$$\partial \pi^{TPS} / \partial q: \ C_q = p + \beta t, \tag{5}$$

where $-C_e$ and C_q represent the private marginal cost of emissions reductions and production, respectively.[18] Condition 4 indicates that profit maximization requires that the marginal cost and benefit of abatement be equal. Condition 5 indicates that the marginal cost and benefit of production must be equal. The marginal benefit is the price of output plus βt, the increment to profit from selling the β additional allowances generated by a unit increase in output. The βt term is the implicit subsidy to an increase in output—or implicit tax on a reduction in output—under the TPS.

Under C&T, the profit function for electricity generators is

$$\pi_{ELEC}^{C\&T} = \overline{pq} + p(q - \overline{q}) - C(q,e) - t(e - \overline{a}), \tag{6}$$

[17] Increasing output adds to profit when it does not raise production cost more than the value of the new allowances.
[18] Despite the administered pricing of electricity, only the market price *p* appears in Equation 5 because the marginal output of electricity is sold at market prices.

where $\overline{a}$ denotes the fixed number of allowances allocated to the firm. The difference from the TPS's profit function is in the far-right term, in which the allowance allocation is the exogenous quantity $\overline{a}$. The profit functions under C&T for the electricity generators and the nonelectricity sectors are

$$\pi_{ELEC}^{C\&T} = pq + (\overline{p} - p)\overline{q} - C(q,e) - t(e - \overline{a}) \tag{7}$$

$$\pi_{NON-ELEC}^{C\&T} = pq - C(q,e) - t(e - \overline{a}) . \tag{8}$$

The profit-maximizing first-order conditions under C&T for both electricity and nonelectricity firms are

$$\partial \pi^{C\&T} / \partial e: \; -C_e = t \tag{9}$$

$$\partial \pi^{C\&T} / \partial q: \; C_q = p . \tag{10}$$

Conditions 4 and 9 are identical: under both the TPS and C&T, profit maximization requires that the marginal cost of emissions equal the allowance price *t*. Conditions 5 and 10 are different, however. In contrast with C&T, the TPS introduces the implicit subsidy to output (or tax on output reduction) βt. For any given allowance price, the subsidy gives firms incentives for higher output than under C&T. It is straightforward to show that the first-order conditions of C&T match those of a social planner (Tietenberg, 1985), whereas the TPS encourages output levels above the socially optimal level.[19] Correspondingly, the TPS does not make sufficient use of output reduction as a channel for achieving compliance and instead relies excessively (from the perspective of cost-effectiveness) on reductions in emissions intensities. This diminishes the TPS's cost-effectiveness.[20]

The size of the cost-disadvantage of the TPS depends on the variation of benchmarks. Higher variation leads to greater differences in the implicit output subsidy, which tends to cause greater variation in the marginal cost of production across firms. This leads to a further sacrifice of cost-effectiveness. However, as noted, the disadvantage is mitigated by pre-existing taxes on factors and other production inputs. Owing to its implicit output subsidy, the TPS leads to smaller increases in output prices compared to an equivalently stringent C&T system. Consequently, the distortions from these pre-existing taxes and associated cost-effectiveness disadvantage are smaller.

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[19] However, with pre-existing distortionary taxes, the first-order conditions for private cost-minimization under C&T do not match the social planner's cost-minimization conditions. See, for example, Bovenberg and Goulder (1996).
[20] See Fischer (2001) and Goulder et al. (2022) for discussion of the significance of the implicit output subsidy.

Notwithstanding its disadvantages in terms of cost-effectiveness, the TPS has certain attractions relative to C&T. First, it would likely give rise to lower emissions leakage. Its implicit output subsidy leads to smaller increases in the prices of the output of the covered facilities than under C&T. As a result, it induces a smaller shift in demand toward the output of firms in the noncovered industries and less associated leakage.[21] Second, because allowance allocation under the TPS is endogenous to the level of output, the policy is responsive to macroeconomic conditions. When the economy is booming (contracting) and levels of production increase (decrease) in response to the demand, the number of allowances allocated automatically increases (decreases), moderating the potential changes in the allowance price. Third, the TPS's rate-based structure capitalizes on China's experience with intensity-based environmental regulation.

3. The Numerical Model

3.1. Main Features

The multisector dynamic computable general equilibrium (CGE) model developed for this study considers a range of economic factors that determine the TPS's cost-effectiveness and distributional outcomes. As Figure 1 shows, the model captures the interactions among China's production, household, and government sectors. Representative firms in each of the 31 production sectors employ inputs of primary factors (capital, labor, and natural resources) and intermediate inputs (energy and material goods) to produce goods for the domestic market and export. We recognize within-sector differences in production technologies and types of firm ownership. A representative household earns income from returns to the factors of production and devotes that income to consumption and savings. The government receives tax revenues that are devoted to government consumption, public savings, and transfers to households. Private and public savings finance investment. The final demand for goods and services consists of household consumption demand, public and private investment demand, and the government's demand for goods and services. The model also incorporates emissions allowance trading. For each year in the interval 2020–2035, it solves for the equilibrium factor prices, allowance prices, and the prices of all produced goods.

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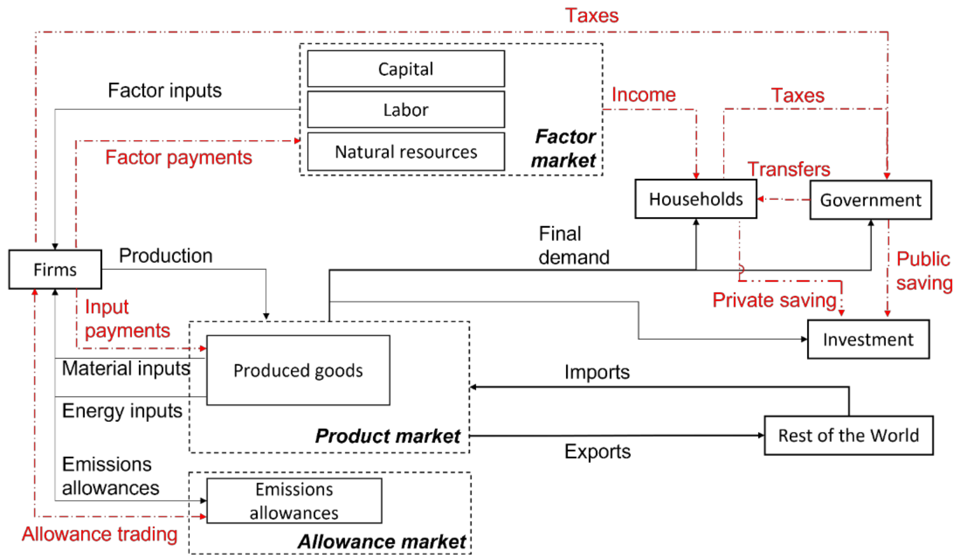
[21] See Fowlie and Reguant (2022) for a cogent analysis of emissions leakage from incomplete markets for CO_2.

Figure 1. Goods and Financial Flows



Note: The solid and dashed lines with arrows indicate the material flow and cash flow in the economy, respectively.

The model differs from most other general equilibrium models by recognizing heterogeneity in production methods within sectors. It exploits information from a unique firm-level dataset on emissions, output, and energy use obtained from the MEE. This enables it to analyze the TPS's impacts on firms of different emissions intensities within a given sector.

The model considers important interventions in the market by China's governmental authorities. These include the administered pricing of some of the electricity supplied, the preferential treatment of SOEs, subsidies targeted toward renewable electricity, and pre-existing taxes on factors or production.

3.2. Production

Here we briefly describe the structure of the production system. Appendix A provides details.

3.2.1. Primary Factors

The primary factors are labor, capital, land, and "natural resources." Labor and capital are employed in production in all sectors. Labor is perfectly mobile across sectors. Capital is imperfectly mobile: there are costs to its reallocation across sectors or subsectors or between SOEs and privately owned enterprises (POEs). Land is employed in the agriculture sector only and is not mobile across sectors. Natural resources are directly employed only in wind, solar, hydroelectric, and nuclear electricity production and are not mobile across sectors or subsectors.

3.2.2. Sectors and Subsectors

Table 1 identifies the model's 31 production sectors. Some sectors subdivide into subsectors. In the electricity sector, the model distinguishes renewable electricity (solar, wind, and hydroelectric) and nuclear electricity from fossil-based electricity. Within the group of fossil-based electricity generators, the model recognizes heterogeneity across plants by distinguishing 11 technology categories. The cement, aluminum, and iron and steel sectors also have subsectors (see Appendix B for the rationale and method for these classifications) with differing production technologies and associated input intensities. Notwithstanding the differences in input intensities across subsectors, the outputs from subsectors of a given sector are treated as homogeneous and face the same market price. Production is represented by nested constant elasticity of substitution (CES) functions. Each sector or subsector employs material inputs, energy, and factor inputs for production.

Table 1. Sectors

Name	Description
Cement[a]	Cement
Iron and steel[b]	Iron and steel
Aluminum[c]	Aluminum products
Pulp and paper	Pulp and paper
Other nonmetal products	Nonmetal processing other than cement
Other nonferrous metals	Nonferrous metals other than aluminum
Raw chemicals	Raw chemical materials, chemical products
Agriculture	Crop cultivation, forestry, livestock products, and fishery
Mining	Metal minerals mining and nonmetal minerals, and other mining
Food	Food and tobacco
Textile	Textile
Clothing	Clothing
Log and furniture	Log and furniture

Printing and stationery	Printing and stationery
Daily chemical products	Chemical fibers, medicines, rubber, and plastics products
Metal products	Metal products
General equipment	General equipment manufacturing
Transport equipment	Transport equipment manufacturing
Electronic equipment	Electronic equipment manufacturing
Other manufacturing	Other manufacturing
Water	Water
Construction	Construction
Transport	Transport and post
Services	Services
Electricity[d]	Electricity generation
Petroleum refining	Petroleum refining
Heat	Heat distribution
Coal	Coal mining and processing
Crude oil	Extraction of crude oil
Natural gas	Primary production of natural gas
Gas manufacture and distribution	Manufacture, processing, and distribution of natural or synthetic gas
Heat	Heat distribution

[a] This divides into three subsectors: high-, medium-, and low-efficiency cement production.

[b] This divides into six subsectors: high-, medium-, and low-efficiency basic oxygen steel production and high-, medium-, and low-efficiency electric-arc furnace steel making.

[c] This divides into three subsectors: high-, medium-, and low-efficiency aluminum production.

[d] This divides into 15 subsectors, distinguishing the following generation technologies: LUSC (1,000MW Ultra-supercritical), SUSC (600MW Ultra-supercritical), LSC (600MW Supercritical), SSC (300MW Supercritical), LSUB (600MW Subcritical), SSUB (300MW Subcritical), OTHC (Installed capacity less than 300MW), LCFB (Circulating Fluidized Bed Units with installed capacity greater than or equal to 300MW), SCFB (Circulating Fluidized Bed Units with installed capacities less than 300MW,; HPG (Gas-fired plants, F-class), LPG (Gas-fired plants, Pressure lower than F-class), Wind power, Solar power, Hydropower, and Nuclear power.

3.2.3. State-Owned Enterprises and Administered Pricing

SOEs are an important feature of the Chinese economy. They account for around 31 percent of the value of economywide output. SOEs receive favorable treatment relative to POEs through subsidies to their various inputs. They are especially important in the crude oil and electricity sectors, where they account for more than 87 percent of the output value (see Table C3 in Appendix C).

We model the SOEs and POEs as profit-maximizing firms that enjoy subsidies and face taxes. The functional forms of both types of firms are the same, but the parameters differ. Both the subsidies and taxes are regarded as exogenous from the point of view of the firm. SOEs benefit from preferential treatment through input subsidies. Also, individuals employed in SOEs often receive superior benefits, including higher social security payments and pensions.[22] Government-provided transfers defray a significant fraction of the costs of these benefits.

A challenge to modeling SOEs and POEs is their coexistence in specific markets. Despite the SOEs' preferential treatment and associated lower average costs of production, the SOEs do not take over the markets, as optimal supplies depend on marginal rather than average costs. In the model, marginal costs increase with supply, reflecting the fact that both types of firms rely on imperfectly mobile capital as an input and experience the associated diminishing marginal productivity of production. For a given type of output, both SOEs and POEs choose levels of output that bring their marginal costs up to the prevailing and common output price. Appendix A provides details.

As was noted, the model incorporates the administered pricing in China's electricity market and the nation's ongoing electricity market reform. As Equation 2 indicates, generators sell a fixed amount of their electricity at a government-administered price (usually higher than the market price) and sell the production beyond that at market prices. Administered pricing is expected to apply only until 2025, as ongoing reform indicates a fully liberalized electricity market by then. Appendix A provides further details.

[22] Literature that provides evidence on these preferential treatment to SOEs includes Guariglia et al. (2011), Song et al. (2011), Démurger et al. (2012), Hsieh and Song (2015), Berkowitz et al. (2017), Harrison et al. (2019), and Han et al. (2021).

3.3. Household Behavior

A representative household's consumption choices reflect its utility maximization subject to a budget constraint. A nested CES utility function governs the allocation of consumption expenditure across specific consumer goods.

The household receives income from labor, capital, land, and natural resource rents and devotes its income to consumption and private savings. Private savings are devoted to investment—expenditure on an investment good. The savings rate is a positive function of the return on investment.

3.4. Government Behavior

The government sector comprises government behavior at all levels: national, regional, and municipal. The model's taxes include output taxes and subsidies, intermediate taxes and subsidies, factor taxes and subsidies, final demand taxes, import tariffs, export subsidies, and subsidies for wind and solar electricity generation. Government expenditure consists of government savings, public consumption, and transfers to households. Public consumption is set as a fixed share of GDP and characterized by a CES preference function defined over the material-energy composite. The government must balance its budget in each period; its transfers are endogenously determined and adjusted to meet the budget balance requirement.

Appendix A offers details of the three CES preference structures for consumption, investment, and government spending, respectively.

3.5. Foreign Trade

The model regards China as a price-taker on the world market: the foreign-currency prices of imports are exogenous, as are the foreign-currency prices at which exports can be sold. Domestically produced and imported goods in a given sector category are regarded as imperfect substitutes; hence their market prices can differ. Import and export quantities are functions of the relative prices of domestic and foreign goods.

The time profile of international financial capital flows is specified exogenously, based on Ju et al. (2021). The exchange rate adjusts each year to equate the value of net exports with the net inflow of international financial capital.[23]

[23] A more sophisticated treatment of international trade could grant China monopsony power in international markets and incorporate international financial capital flows endogenously. We believe that these extensions would have little influence on our main results. The TPS-covered sectors account for only 7 percent of the total exports in China, which suggests that the TPS-induced price changes in these sectors would have only a minor impact on China's terms of trade and GDP.

3.6. Equilibrium

The general equilibrium requires supply–demand balance in each period for each factor and produced goods. Under policies with emissions allowance trading, the allowance supply and demand must match as well. In each period, these requirements determine (a) the prices for the 31 sectors' produced goods; (b) the wage rate; (c) the pretax rental prices of capital, which differ across sectors (and subsectors in the electricity, cement, aluminum, and iron and steel sectors); (d) the rental prices of the natural resources employed in the solar, wind, hydroelectric, and nuclear electricity production subsectors, respectively; and (e) the CO_2 allowance price.

3.7. Dynamics

The model solves at one-year intervals for 2020–2035.[24] Changes in equilibria from one period to the next depend on the increments to the stocks of labor and capital. There is one aggregate capital stock. The stock in the next period is aggregate real investment in the current period net of depreciation over that period. The stocks of land and the four kinds of natural resources (wind, solar, hydroelectric, and nuclear) are treated as fixed at the base year level.

Technological progress takes two forms: autonomous energy-efficiency improvement (AEEI) and Hicks-neutral technological change. AEEI is an exogenous increase in the productivity of the composite energy input into production. As indicated below, the AEEI rate differs across sectors. Hicks-neutral technological change applies to all sectors but at different rates across sectors. These differences give rise to structural change in China—in particular, the transition involving increased representation of the service sector (Święcki, 2017) and increased penetration of renewable electricity. The rates of Hicks-neutral technological change are calibrated to match the projections in the State Information Center (2020) and IRENA (2019) (see Appendix C).

4. Data and Parameters

4.1. Data

We combine data from several sources to create a consistent database for inputs, outputs, and emissions. China's 2017 input-output table (NBS, 2018a) offers data on inputs and outputs of production sectors as well as levels of household consumption, government consumption, and investment. The Global Trade Analysis Project (GTAP 10) database (Aguiar et al., 2019) offers information on taxes and subsidies on inputs and goods. CO_2 emissions from production are derived from the sectoral energy use data in the 2017 China energy balance table (NBS, 2018b). We updated the input and

[24] The model is solved as a mixed complementarity problem with a Newton-based solver.

output data so that the GDP, total CO_2 emissions, value-added shares of the service sector and agriculture sectors, and total tax revenue net of subsidies match the published statistics in 2020 (NBS, 2021). We disaggregated the sectoral data into subsectors for electricity, cement, aluminum, and iron and steel according to the subsector-level information obtained by aggregating firm-level data collected by the MEE. These data provide production, fossil fuel energy consumption, electricity usage, heat rate, and CO_2 emissions at the plant level. The plant-level data spans the electricity, cement, aluminum, and iron & steel sectors.

Data on the costs of changing the heat rates of fossil-based power plants are from a series of reports by the National Development and Reform Commission of China (NDRC, 2016, 2017). Data on the costs of adding renewable electricity capacity are from Zhang et al. (2023).[25] Data on administered pricing of electricity are from the China Electricity Council (CEC, 2019). Key data pertaining to SOEs and POEs are from the Chinese Industrial Enterprise Database (NBS, 2017) and literature (Han et al., 2021). The database offers information on SOE and POE's output shares and capital-output ratios in each sector, and Han et al. (2021) offer information on the additional subsidies received by the SOEs as compared with POEs. Appendix B provides details on data sources and processing steps.

4.2. Parameters

We make use of the data from these sources and others to obtain key parameters of the model. Appendix C provides the details.

Elasticities of substitution among various fuel inputs are from Cossa (2004) and RTI ADAGE (RTI International, 2015). The elasticities of substitution among various factor inputs are from Jomini et al. (1991). Elasticities of substitution between domestic and imported goods are from Hertel et al. (2007). Elasticities of capital transformation are from the GTAP database (Aguiar et al., 2019).

Additional parameters are obtained through calibration. Input share parameters of production functions were identified by the requirement that the inputs and outputs in each sector in the base year be consistent with the benchmark input-output table. Parameters for the shares of capital inputs in SOEs and POEs were identified by the condition that marginal costs of production be the same at the given market's output price.

In subsectors of the electricity sector, the substitution elasticities between the energy and factor composites are calibrated to ensure that, in the baseline simulations, subsector-level marginal costs of reducing heat rates match points on a separately derived curve for subsector-level costs of reducing heat rates. We derive the separate

[25] Wind and solar electricity generation incurs integration costs, which include grid integration, balancing services, flexible operation of thermal plants, and reserve costs. The integration costs increase as the wind and solar penetration levels rise (see Appendix C).

cost curve from the series of reports by NDRC (2016, 2017), as mentioned in Subsection 4.1. For renewable electricity production, both the elasticity of substitution between the natural resource input and other inputs and the share of natural resource input are calibrated so that the marginal cost (the sum of generation and integration costs) at various renewable electricity supply levels matches the marginal cost curve inferred from the estimations by Zhang et al. (2023). The substitution elasticities between electricity and non-electricity inputs in all sectors are calibrated to yield a demand elasticity for electricity consistent with empirical evidence in China (Hu et al., 2019). The substitution elasticities between consumption and private savings are calibrated so that the demand elasticity of investment goods matches the empirical evidence (Lian et al., 2020).

The time profile of effective labor is exogenously specified so that the model's GDP growth rate in the baseline is consistent with official projections.[26]

5. Scenarios

We examine the TPS's impacts in its three planned phases. The first began in 2020 and covers only the electricity sector (which accounted for about 43 percent of China's total CO_2 emissions in 2020). The assumed coverage in later phases is based on discussions by decisionmakers in the MEE and other administrative bodies. The second phase is assumed to begin in late 2023, with the TPS expanding to also cover the iron and steel, aluminum, and cement sectors (which currently account for about 67 percent of CO_2 emissions). The third phase begins in 2026, with coverage expanding further to include the pulp and paper, other nonmetal products, other nonferrous metals, raw chemicals, and petroleum refining industries.[27]

Table 2 describes the policy cases considered. We examine cases that differ in the number and stringency of benchmarks and cases in which some of the emissions allowances are supplied via auction. Case 1 (the central case) aligns most closely with current plans by MEE in initial benchmark values and rates of benchmark tightening over time. Table C6 in the Appendix provides the benchmark values in the various policy cases.

[26] These projections are in State Information Center (2020). We calibrate the model to yield GDP growth rates of 5.5, 4.5, and 3.5 percent in 2020–2025, 2026–2030, and 2031–2035, respectively, consistent with these projections.
[27] Other nonmetal products include ceramics, bricks, and glasses; other nonferrous metals include copper and tin; raw chemicals include ethylene, methanol, synthetic ammonia, caustic soda, soda ash, synthetic fiber, and plastic; refined petroleum products include gasoline and diesel fuels.

Table 2. Policy Cases Considered

Case	Specification
Case 1: Central case	**Number of benchmarks.** Four benchmarks apply to the electricity sector: three for coal-fired and one for gas-fired generators. Two apply to the iron and steel sector.[a] One applies to each of all other sectors.
	Initial benchmarks. Initial benchmarks for the electricity sector are set according to the MEE's released documents. Initial benchmarks for other sectors are set to be 2.5% below their emissions intensity in the year before they are included in the TPS.
	Tightening rates of benchmarks. The tightening rate for the electricity sector is 0.5%/year during Phase 1 according to the MEE. We assume it is 1.5% in Phases 2 and 3 and that the rate for other sectors is 2.5%.[b]
Case 2: Fewer electricity sector benchmarks	**Case 2a:** Two-benchmark case: One benchmark for coal-fired and one for gas-fired generators. All other benchmark assumptions are the same as in Case 1. The coal-fired generators' benchmark is the weighted average of their differing benchmarks in Case 1. All benchmarks are scaled by a common factor to match Case 1's economywide emissions each year.
	Case 2b: One-benchmark case: A single benchmark for all generators. The settings of all other benchmark assumptions are the same as in Case 2a.
Case 3: Introduction of allowance auction	**Auction share.** The auction starts in 2025. The initial share of auctioned allowances is 10 percent for the electricity sector and 0 percent for others. The share increases by a constant rate in the electricity sector and a different constant rate in the other sectors, reaching 100 percent for the electricity sector and 30 percent for other covered sectors by 2035. The benchmarks that determine free allowances are lowered to match Case 1's economywide emissions in each year.
	Recycling of auction revenues. • **Case 3a:** recycled as output subsidies for wind and solar electricity. • **Case 3b:** recycled as lump-sum transfers. • **Case 3c:** recycled to finance cuts in capital and labor taxes in all sectors.

[a] One for the basic oxygen process and one for the electric-arc furnace process.

[b] The lower tightening rate for the electricity sector is consistent with the MEE's view that less room remains for future energy-efficiency improvements in this sector than in others.

6. Results

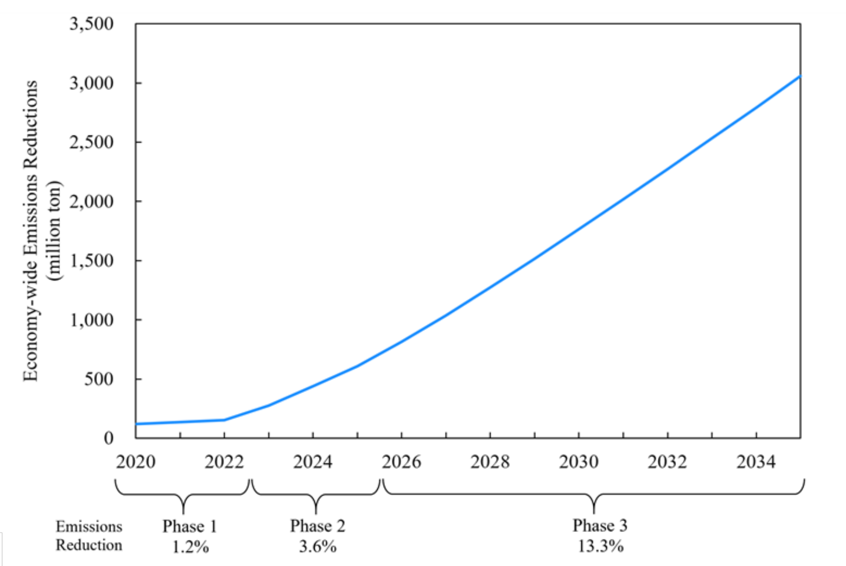
6.1. Aggregate Impacts

6.1.1. Emissions Reductions

Figure 2 displays the policy-induced emissions reductions (relative to the baseline) in Case 1. As indicated in the figure, the reductions in CO_2 emissions become progressively larger as the system's coverage expands and the benchmarks are tightened. The average annual reduction during Phase 2 is about 441 million tons, more than three times the average annual reduction during Phase 1; in Phase 3, the average reduction is about 1.9 billion tons, about four times the average during Phase 2.[28] In 2035, the reduction is about 20 percent relative to the baseline. Below we will show that maximizing net benefits from emissions reductions would call for more stringent benchmarks and associated policy stringency.

In Phase 1, by far the largest changes in emissions are in the covered sector (electricity), where emissions decline annually by about 137 million tons, or 3 percent from the baseline.

Figure 2. Emissions Reductions Relative to the Baseline, over Time

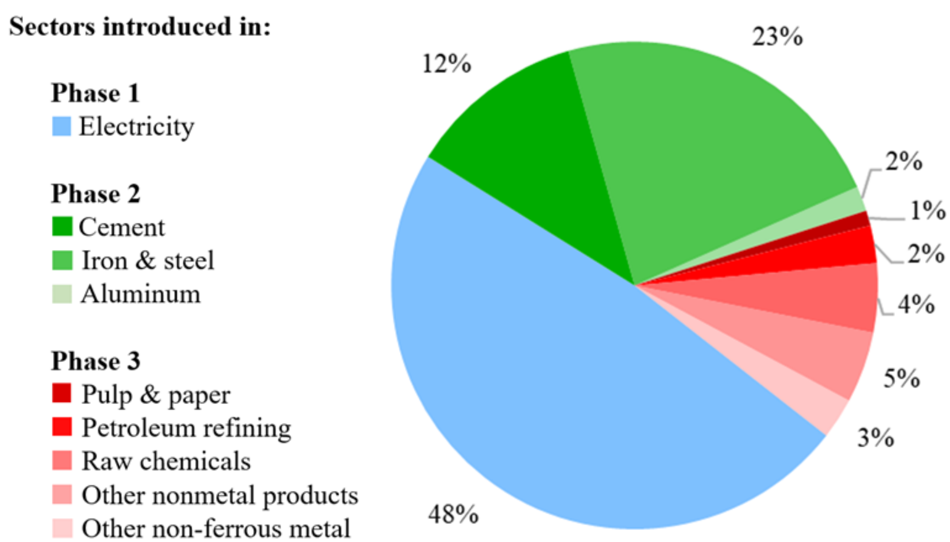


[28] Under China's TPS, the emissions associated with electricity production are priced twice: the electricity sector faces the price of emissions from its generation of electricity, and nonelectricity sectors are also charged for the emissions from generating the electricity they use as an input in production. This deliberate double-counting is intended to encourage high-electricity-consuming industries to further reduce emissions, to offset the reduced incentives to improve electricity-use efficiency because of the free allocation of allowances and the administered prices for some electricity. The simulations in this study incorporate administered pricing and double-counting.

Emissions from uncovered sectors increase slightly—by 0.8 million tons annually. This increase mainly reflects the slightly higher use of coal in these sectors because of the lower coal prices stemming from the significant reduction in coal demand by the electricity sector. Over all of 2020–2035, the cumulative reduction is estimated to amount to 21 billion tons, or 9.7 percent of the cumulative baseline emissions.

Figure 3 shows the covered sectors' relative contributions to emissions reductions, 2020–2035. The largest reductions are from the electricity sector and the sectors added in Phase 2, with the former accounting for 48 percent and the latter collectively accounting for 37 percent of the total. The TPS gives rise to a small amount of emissions leakage—a slight (0.2 percent) increase in emissions from uncovered sectors, reflecting the aforementioned increase in the demand for coal by these sectors.[29]

Figure 3. Covered Sectors' Cumulative Emissions Reductions, 2020–2035



[29] This includes increased emissions from eventually covered sectors during the earlier periods in which they were not yet covered.

6.1.2. Aggregate Costs

1. Impact under the TPS

Table 3 presents the aggregate costs of the TPS, measured by both the change in GDP and the equivalent variation measure of the change in household utility. The GDP cost is relatively small (less than 0.01 percent) in Phase 1 but expands significantly over time, a consequence of increased benchmark stringency and broader sector coverage. The present value of the GDP cost over the interval 2020-2035 is 2.0 trillion RMB, 0.13 percent of the baseline GDP. When measured via the equivalent variation, the cost is smaller, largely because this measure is based on changes in consumption and disregards the significant declines in investment. The TPS's negative impacts on investment are substantial because the main inputs into the production of the composite investment goods are iron and steel and cement, which are emissions intensive and covered by the TPS. In Subsection 6.3, we compare these costs with estimates of the environmental benefits.

Table 3. Summary of Costs of Case 1

	Cost (billion RMB)		CO_2 emissions abatement (billion tons)	Cost per ton of CO_2 abatement (RMB/t)	
	Measured by the change in GDP	*Measured by the equivalent variation of consumption*		*Measured by the change in GDP*	*Measured by the equivalent variation of consumption*
Phase 1 (2020–2022)	17	8	0.4	41	21
Phase 2 (2023–2026)	63	10	1.3	48	8
Phase 3 (2026–2035	1,939	477	19.1	102	25
Overall (2020–2035)	2,019	495	20.8	97	24

We have also explored the significance of the SOEs to aggregate costs. We considered the TPS's impact in a counterfactual case in which SOEs do not receive favorable treatment. The TPS's GDP costs in this case are 0.8 percent higher than that in the case with preferential treatment. This is because the distortionary impacts of the TPS's implicit output subsidy are smaller when the SOEs receive favorable treatment. Given that SOEs have lower output supply elasticities than POEs,[30] the ratio of SOE to POE output is lower in the absence of preferential treatment compared to the case with preferential treatment. This lowered ratio increases the average supply elasticity in covered sectors. As a result, the distortionary impacts of the implicit output subsidy are larger in the preferential treatment case, leading to a higher GDP cost.

2. Comparison with C&T

An important choice for policymakers considering emissions trading is whether to adopt the rate-based TPS or the mass-based and more widely used alternative of C&T. China's policymakers have been seriously considering switching from the TPS to C&T.

Figures 4a and 4b display the allowance prices and economic costs of the two approaches, showing some important changes over time. In 2020, the model-generated allowance price is 58 RMB/ton, close to the observed price in the first compliance period, which is 40–60 RMB/ton. The rising trajectory of the price in Figure 4a reflects the combination of benchmark tightening and broader coverage of the TPS over time.[31]

Figure 4b reveals that the relative costs of the TPS and C&T follow a dynamic pattern that, to our knowledge, has received no prior attention. The TPS's costs are close to those of an equally stringent C&T system during the first two phases but exceed C&T costs in later years.[32]

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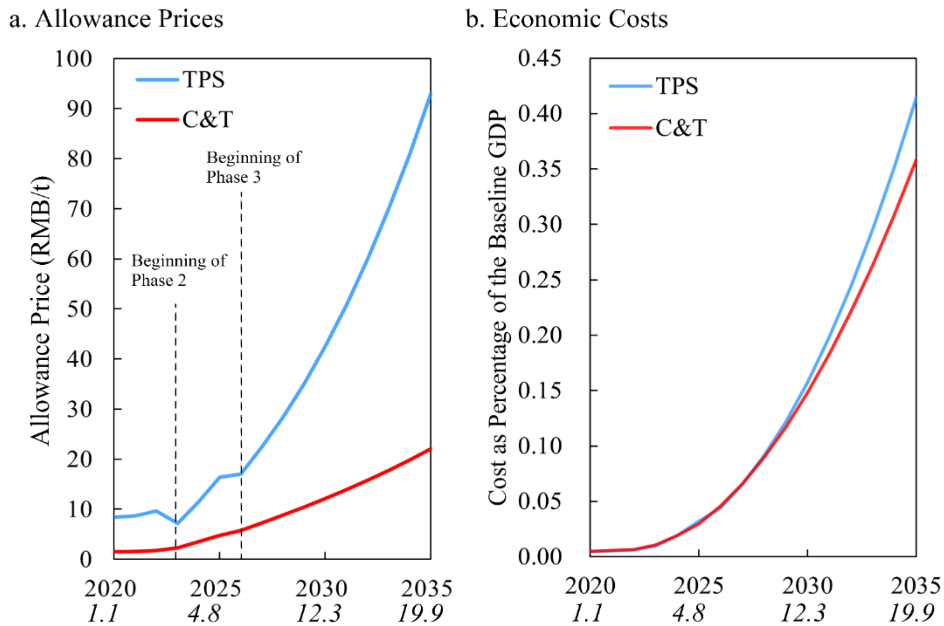
[30] This is because SOEs have higher intensities of sector-specific (or subsector-specific) capital input than POEs, which makes it harder for SOEs to adjust their output in response to a change in producer price. Hence, within the same sector (or subsector), SOEs exhibit lower supply elasticities.

[31] The slight dip in the price from 2022 to 2023 reflects a short-term reduction in the overall stringency of the TPS during the transition from Phase 1 to Phase 2.

[32] In the simulations of C&T, emissions allowances are allocated for free in each year so that economywide emissions match those of the TPS in Case 1. The distributions of the allocations across sectors and subsectors are proportional to those under the TPS.

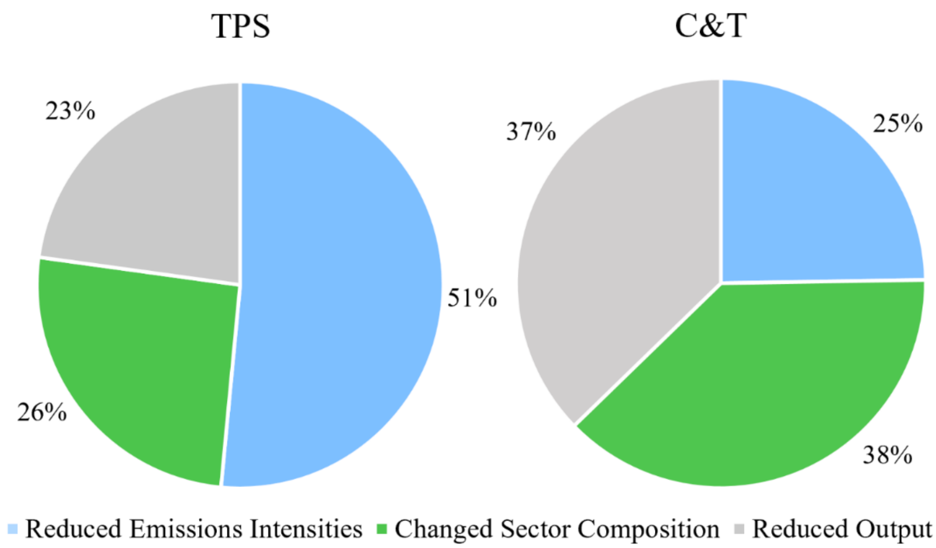
Figure 4. Carbon Price and Economic Costs over Time



Note: Numbers in italics are percentage emissions reductions from the baseline.

Three factors underlie this pattern. First, as noted in Section 2, the TPS introduces an implicit subsidy to output, which causes covered facilities to make relatively inefficient use of the output-reduction channel to reduce emissions. Figure 5 displays the relative contributions of the three key channels for emissions reductions over the 2020-2035 interval under the TPS and an equally stringent C&T system. Compared with C&T, covered facilities rely less on the output-reduction channel and more on reduced emissions intensities, which explains why allowance prices rise more under the TPS than under C&T (see Figure 4a). The higher output relative to C&T is associated with a higher demand for allowances, which leads to higher allowance prices despite the TPS's lower emissions intensity.

Figure 5. Sources of Emissions Reductions under the TPS and Cap and Trade



Our model reveals two other previously unrecognized factors at work. One is policy stringency, which explains the widening gap between the policies' costs over time. Equation 5 of the analytical model indicated that the inefficiency associated with the TPS's implicit subsidy is proportional to the product of the benchmark and the allowance price. Greater stringency generally implies a higher allowance price, which augments the importance of the implicit subsidy.[33] Figure 4b's results suggest that the magnitude of this inefficiency is not great until Phase 3, when higher allowance prices cause this product to be considerably higher.

A further and important additional factor is the presence of taxes on factors of production. This factor reduces what otherwise would be a larger cost-disadvantage of the TPS. As mentioned in the introduction, although the TPS's implicit output subsidy leads to inefficiently small output reductions relative to C&T, it also has the *beneficial* effect (in terms of efficiency) of reducing the distortionary effect of pre-existing taxes and renewable subsidies. This "tax-interaction" effect has been examined theoretically and numerically in the public economics and environmental economics literature.[34] This beneficial impact of the subsidy offsets the cost-effectiveness disadvantage stemming from the TPS's limited use of output-reduction

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[33] In our TPS simulations, allowance prices rise over time by a larger percentage than the percentage by which the benchmarks decline. Hence, the product of the allowance price and benchmark grows, increasing the associated distortion.

[34] See, for example, Bovenberg and Goulder (1994), Goulder et al. (1999), Parry and Bento (2000), Fullerton and Metcalf (2001), and Parry and Williams (2011). To confirm the significance of pre-existing taxes for the relative costs of the TPS and C&T, we performed counterfactual simulations in which these taxes' magnitudes on factors and other inputs are different (see Appendix D).

as a channel for reducing emissions. In the first years of the TPS, the opposing effects on cost-effectiveness are comparable; hence, the costs of each policy are not much different. However, over time, as the product of the allowance price and benchmark increases, the adverse impact from this product becomes significantly more important than the beneficial impact of pre-existing taxes, and the gap between the TPS and C&T costs widens. We simulate counterfactual cases where the levels of pre-existing taxes differ from Case 1. The results (see Appendix D) indicate that the ratio of TPS to C&T costs declines monotonically as the levels of pre-existing taxes are raised.

The impact of prior taxes has significant policy implications, suggesting that the TPS need not be viewed as having a large cost-disadvantage relative to C&T in settings with significant factor taxes. As shown in Figure 4b, the disadvantage is negligible during the first decade of China's TPS, but with increased stringency and associated increases in allowance prices, it becomes significant.[35]

6.2. Sector Impacts

6.2.1. Sector and Subsector Prices, Outputs, and Profits

Table 4 displays, for each sector and phase, the percentage changes in the output price, level of production, and profit.[36] Prices and profit are expressed in real terms, with the price of a composite produced good employed as the price index.

As expected, the covered sectors tend to experience the largest reductions in output, reflecting the use of output-reduction as a channel for reducing compliance costs. That reduction is highest in the electricity sector; its intensity is relatively high and its benchmarks are stringent relative to those of other sectors.[37] As a result, its unit costs increase significantly, prompting a significant reduction in electricity demand.

[35] China's planners are contemplating a transition from the TPS to C&T. We have performed simulations of such a transition and find that it can lower the cost per ton of emissions reductions (see Appendix E).

[36] We measure the sectors' profit by the total after-tax return to the sectors' capital and the value of free allowances.

[37] The emissions intensities by sector are provided in Table B6 in Appendix B.

Table 4. Percentage Changes of Price, Quantity, and Profit Impacts of Case 1

Sector	Price			Output			Profit		
	Phase 1	*Phase 2*	*Phase 3*	*Phase 1*	*Phase 2*	*Phase 3*	*Phase 1*	*Phase 2*	*Phase 3*
Electricity	**0.22**	**0.47**	**3.80**	**-0.39**	**-0.86**	-6.74	0.73	1.49	4.35
Cement	-0.02	**0.75**	**9.96**	-0.02	**-0.10**	**-0.82**	-0.04	**5.18**	**16.8**
Iron and steel	-0.01	**0.14**	**0.57**	-0.04	**-0.28**	**-0.76**	-0.04	**2.41**	**7.90**
Aluminum	0.10	**0.43**	**4.12**	-0.12	**-0.51**	**-4.98**	-0.06	**2.54**	**6.61**
Pulp and paper	0.01	0.00	**0.24**	-0.02	-0.04	**-0.40**	-0.02	-0.04	**2.42**
Petroleum refining	0.00	0.00	**0.13**	-0.04	0.04	**-0.19**	-0.05	0.04	**0.58**
Raw chemicals	0.00	-0.01	**0.54**	-0.03	-0.04	**-1.37**	-0.03	-0.06	**2.02**
Other nonmetal products	0.01	0.05	**0.66**	-0.02	-0.09	**-0.75**	-0.02	-0.10	**1.28**
Other nonferrous metal	0.01	0.04	**0.51**	-0.06	-0.19	**-1.53**	-0.06	-0.21	**1.08**
Coal	-0.18	-0.54	-2.09	-1.40	-4.15	-16.5	-2.02	-5.92	-21.8
Natural Gas	0.03	0.09	0.53	0.07	0.19	1.22	0.11	0.29	1.78
Mining	0.01	-0.01	0.05	-0.04	-0.33	-1.55	-0.04	-0.30	-1.08
Agriculture	0.00	-0.02	-0.09	-0.01	0.00	0.01	-0.02	-0.02	-0.05
Uncovered manufacturing[a]	0.00	0.00	0.06	-0.02	-0.08	-0.39	-0.03	-0.09	-0.52
Construction	0.00	0.03	0.33	-0.01	-0.05	-0.46	0.00	-0.06	-0.58
Service[b]	0.00	-0.02	-0.16	-0.01	-0.03	-0.14	-0.02	-0.05	-0.36

Note: The prices and outputs are weighted average percentage changes relative to the baseline in the corresponding period, with annual output levels used as weights. The profits are the present value of cumulative changes in the corresponding period. The green font identifies the covered sectors in the applicable phase.

[a] Elements in this row are percentage changes for the aggregate of all the manufacturing sectors not covered by the TPS. These sectors include food, textiles, clothing, log furniture, printing and stationery, daily chemicals, metal products, general equipment, transport equipment, electronic equipment, and other manufacturing.

[b] We display the results after aggregating the results from the specific service sectors: gas manufacture and distribution, heat distribution, water, transport, and other services.

In all three phases, all sectors covered during the phase in question experience increased profits. This reflects the economic rents associated with the value of the free allowances these sectors receive under the TPS.[38] The rents are significant, as demands for the products of these sectors are relatively inelastic.[39] The low elasticity in part reflects the fact that these sectors are not highly trade-exposed[40]; hence they are less vulnerable to imported substitutes. In the uncovered sectors, impacts on profits and output reflect changes in demand and production cost. The coal sector suffers the highest percentage losses of output and profit, reflecting a significant reduction in demand for coal by the contracting electricity sector. In contrast, the natural gas sector experiences percentage increases in prices, profits, and output. The increased output reflects increased demand for natural gas, which has a lower emissions factor than coal and can substitute for coal in some covered sectors to reduce emissions intensity. Also, the MEE sets less stringent benchmarks (measured by the difference between the benchmark and the baseline emissions intensity) for gas-fired plants than for coal-fired plants, which contributes to the substitution.

For many other uncovered sectors, the TPS raises the costs of production by increasing the prices of their inputs. In Phase 1, this is especially important in the aluminum sector, which is intensive in its use of electricity.

6.2.2. Impacts on Renewables

Many policymakers and citizens hope that China's climate policies will spur the transition away from fossil fuels and toward renewables-based energy. Both the TPS and C&T promote the substitution of renewable-based electricity for fossil-based power. This reflects the fact that both policies raise the prices of carbon-intensive fuel inputs, which raises the marginal costs of fossil-based generation relative to renewables-based generation.[41]

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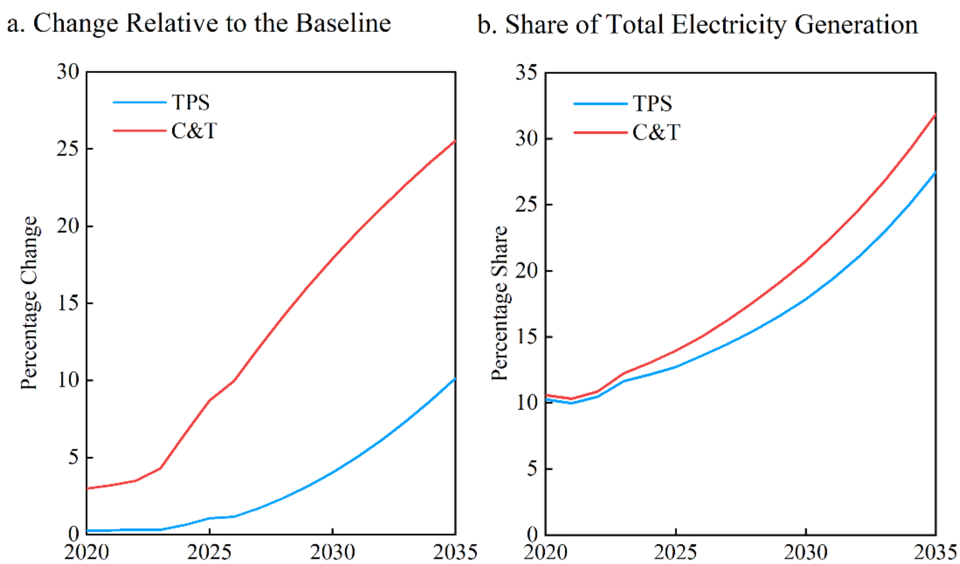
[38] Goulder et al. (2010) offer a detailed discussion of how free allowance allocation yields economic rents. Under the TPS, free allocation is an inherent characteristic of the system: a covered facility with benchmark β receives the quantity βq of free allowances with a value of $t\beta q$. As an example, in the TPS simulations here, the value of the allowances offered free to the electricity sector in 2021 is 257 billion RMB. This fully offsets the TPS-induced increase in production cost to this sector of about 243 billion RMB in that year.

[39] Underlying the overall increase in profits in the electricity sector are differing impacts between the fossil- and renewables-based electricity generators. The former see profit increases during 2020–2028 and reductions during 2029–2035, but the latter experience profit increases during the entire simulation interval.

[40] Table B5 in Appendix B expresses the trade exposure of each sector as the ratio of traded goods to total output.

[41] Over the interval 2020–2035, profits to fossil-based electricity producers decrease by 0.5 percent, although the profits to wind and solar electricity suppliers increase by 10 percent.

Figure 6. Changes in Wind and Solar Electricity Generation Relative to the Baseline



Figures 6a and 6b show the impacts of the two policies on wind and solar generation, as changes relative to the baseline (6a) and as shares of total generation (6b).[42] The shifts toward renewable electricity sources are smaller under the TPS than under C&T. The difference is due to the TPS's implicit output subsidy, which mitigates the increase in fossil-based electricity prices and moderates the substitutions toward renewables-based power.

6.3. Net Benefits

The TPS's climate benefits are estimated to be well above its economic costs. This holds under a plausible range of values for the climate benefits from CO_2 abatement (as implied by alternative values for the SCC), for production parameters[43], and for future levels of stringency.[44]

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[42] The extent of hydroelectric and nuclear electricity generation is mainly determined by government planning in China. Accordingly, the model assumes their outputs remain at the base year levels and are not influenced by the TPS and C&T policies.
[43] As indicated in Section 7, these include elasticities of substitution in production, elasticities of capital transformation, the elasticity of substitution between household consumption and private saving, and the rates of exogenous improvement in energy factor productivity.
[44] To address the uncertainty about future benchmark tightening rates, we consider a low (high)-stringency scenario in which benchmarks are 0.5 percentage points lower (higher) than in Case 1. Section 7 offers details.

We consider three SCC paths[45]: 307 RMB (44 dollars) per ton in 2020, increasing at 3 percent annually (Nordhaus, 2017); 353 RMB (51 dollars) per ton in 2020, increasing by 3 percent annually (Biden administration, 2021); and 1,277 RMB (185 dollars) per ton in 2020, increasing by 2 percent annually (Rennert et al., 2022).

Figure 7a shows the ranges and central estimates of the TPS's costs and climate benefits under Case 1. The estimated benefits from the cumulative CO_2 reductions over the 2020-2035 interval are in the range of 6-43 trillion RMB, 3–22 times the cumulative costs. The central estimate of the climate benefit is 10 trillion RMB, around five times the TPS's costs.

Figure 7b displays the costs and benefits when health benefits from reduced local pollution are accounted for. The health benefits are the estimated values of avoided premature deaths; to estimate them, we apply an emissions-inventory model (Zheng et al. 2019), an air-quality model (Polynomial Function-Based Response Surface Model (Pf-RSM), Xing et al. 2018), and the Global Exposure Mortality Model (GEMM) (Burnett et al. 2018) to calculate $PM_{2.5}$-related premature mortalities under the baseline and the TPS.[46] Appendix F provides the details. The mortality impacts are monetized by considering three sets of assumptions for the value of a statistical life (VSL).[47]

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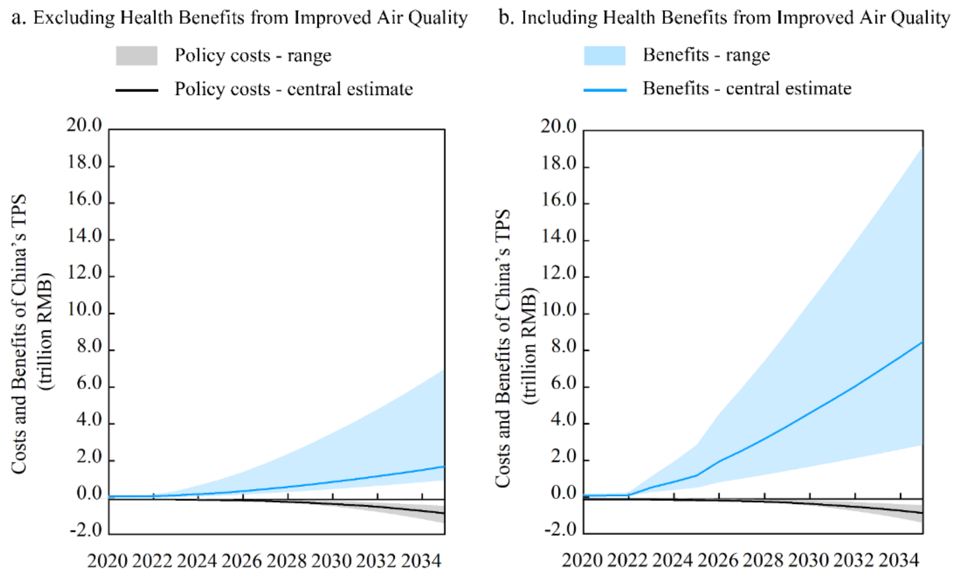
[45] The SCC at time *t* is the climate-change-related cost to the economy, from time *t* into the indefinite future, from the change in climate stemming from an incremental increase in the CO_2 emissions at time *t*.

[46] Studies indicate that $PM_{2.5}$ is a major contributor to premature mortality from air pollution (Burnett et al., 2018; Zhou et al., 2019; Wang et al., 2021). For this reason, we focus on the benefits from reduced $PM_{2.5}$.

[47] We assume a constant elasticity of the VSL with respect to income: $VSL_t = VSL_0(INC_t\ /INC_0)^{\sigma_{VSL}}$, where INC_t and INC_0 are the per-capita income in year *t* and in the base year 2020, calculated from the model's output. VSL_0 and σ_{VSL} are, respectively, the estimated VSL for base year 2020 and the income elasticity of the VSL. The three sets of assumptions for the VSL_0 and σ_{VSL} are 6.5 million RMB in 2020 with a VSL elasticity with respect to per-capita GDP of 0.22, based on Hoffmann et al. (2017); 10.3 million RMB in 2020 with an elasticity of 1, based on OECD (2012); and 18.4 million RMB in 2020, with an elasticity of 0.8, based on EPA (2010).

Figure 7. Costs and Benefits of China's TPS



Accounting for health benefits raises the benefit-cost ratio substantially. The central estimate is that under Case 1, the TPS could avoid 2.3–2.5 million $PM_{2.5}$-related deaths over the 2020-2035 interval, relative to the baseline.[48] Under plausible ranges of the parameters determining the benefits and costs, the present value of the TPS's climate and health benefits stemming from emissions reductions over the interval 2020-2035 interval is in the range of 19-122 trillion RMB. The central estimate is 53 trillion RMB, 26 times the central estimate for the costs.

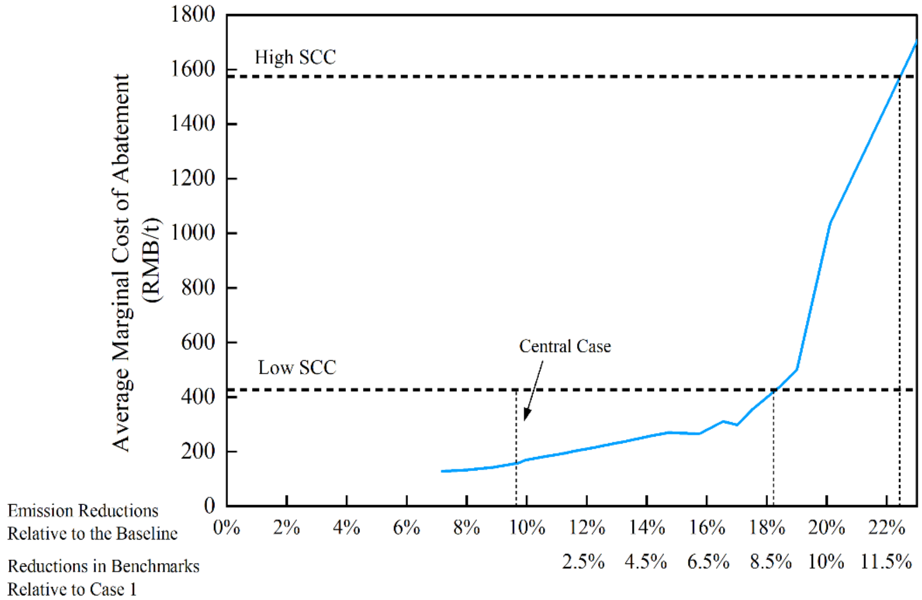
The results in figures 7a and 7b are based on estimated *global* benefits from reductions in CO_2 emissions. Ricke et al. (2018) estimate that China would enjoy approximately 6 percent of these benefits. If only China's climate benefits are considered, the benefit-cost ratio is 0.2–1.3. However, if local health benefits are added, the ratio is consistently well above 1—specifically, 10–68.

A related and important issue is how the TPS's abatement path over the 2020-2035 interval compares with the path that would maximize net benefits over the interval. This requires attention to marginal (rather than total) costs and benefits from abatement. Efficiency maximization requires that marginal costs per ton of emissions reduction equal the SCC. We assess the efficiency of the TPS's stringency level by comparing marginal costs and benefits associated with the emissions reductions over the 2020-2035 interval.[49] We define the marginal benefit as the average value of the

[48] The range is the 95 percent confidence interval implied by uncertainties in parameters in the GEMM model (see Appendix F).
[49] Although the costs are experienced over the interval 2020–2035, the climate benefits stretch into the indefinite future.

SCC[50] over the interval. Marginal cost is derived by decrementing the Case 1 benchmarks each year and noting the associated incremental increase in costs per extra ton abated (see Figure 8). We find that efficiency maximization would require benchmarks approximately 9–12 percent lower than the Case 1 benchmarks. The efficiency-maximizing benchmarks would give yield emissions reductions of around 18–22 percent relative to the baseline, more than twice the scale of the reductions in Case 1.

Figure 8. Average Marginal Cost of Abatement under Alternative Benchmark Stringencies



6.4. Impacts of Auctioning

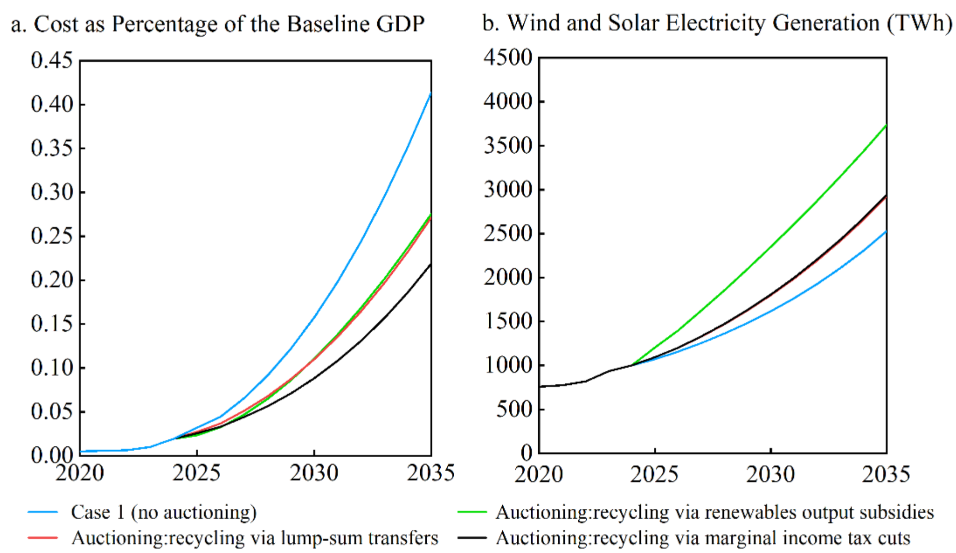
China's policymakers are seriously contemplating revising the allowance allocation method so that some are supplied via auction rather than offered for free. We present results from policy simulations spanning a range of auctioning cases, differing in the ways that the auction revenues are recycled back to the economy. Auctioning is introduced in 2025. For comparability, the total number of allowances supplied in each year is the same with and without auctioning. To maintain the same allowance supply in the auctioning case, the benchmarks (which determine the amounts supplied outside of the auction) are reduced by a common factor across sectors and technology types.

[50] We apply a weighted average of the SCC, with the weight equal to the period's share of the cumulative emissions reductions over the simulation interval. This measure of marginal benefit is conservative in that it does not include health-related cobenefits.

Figure 9 shows economic costs and renewables output in Case 1 and cases involving auctioning—for which the costs are always lower. Introducing auctioning lowers costs because supplying by auctioning does not involve the TPS's implicit output subsidy and its associated distortions. In addition, when the auction revenues are recycled through cuts in marginal rates of pre-existing income taxes, the costs are reduced further, as lowering the marginal tax rates reduces the economic distortions from such taxes. These results provide support on cost-effectiveness grounds for introducing auctioning as part of China's national emissions trading system.

The present value of the gross revenue from the auction is about 2.4 trillion RMB over the interval when the auction is in place (2025–2035). If used as compensation for the coal and mining sectors, which suffer the largest percentage of profit losses, this revenue would fully offset their losses over the same interval (0.9 trillion RMB). As shown in Figure 9b, recycling auction revenues through subsidies to renewables output can yield significant increases in such output.

Figure 9. Wind and Solar Electricity Generation and Economic Costs Under Different Auction Revenue Recycling Options, 2020–2035



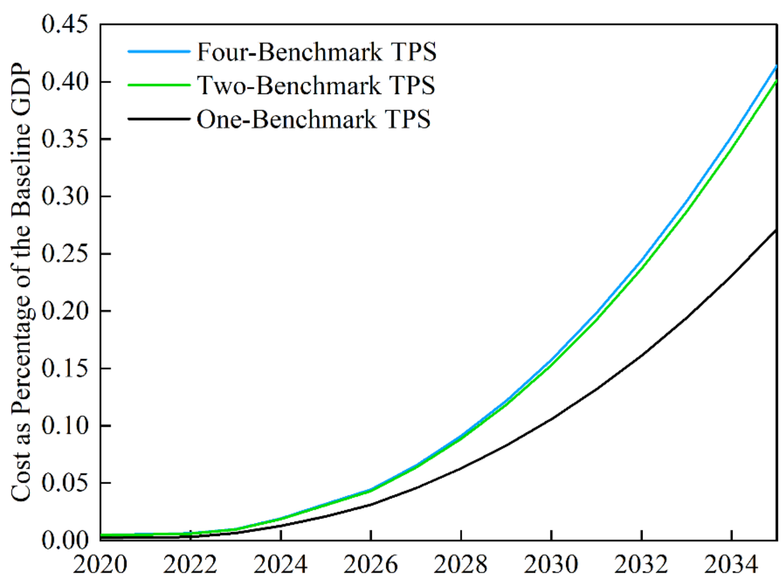
Note: In Figure 9b, the red line and black lines overlap with each other, indicating that recycling in the form of renewable output subsidies has a very slight impact on cost (Figure 9a).

6.5. Trade-offs between Efficiency and Distributional Impacts

One objective of China's policymakers is to achieve emissions reductions at lower costs. Another is fairness—avoiding substantial differences in policy costs across sectors, regions, and demographic types. These objectives can compete with each other. We apply the model to assess the trade-offs.

As indicated in the analytical model, aggregate cost under the TPS depends on the variation of benchmarks. Figure 10 displays the economic costs in cases that differ in terms of such variation. The smaller the number (and greater uniformity) of benchmarks, the lower the cost. Greater uniformity lowers the aggregate cost by reducing the variation in the implicit subsidy and associated wedge between the price of output (or marginal value to consumers) and the private marginal cost of production. This leads to a more efficient allocation of production across generators. Changing from separate benchmarks for coal- and gas-fired generators to a uniform benchmark significantly lowers the costs by narrowing the gap in marginal production costs across generators, which vary prior to the introduction of the TPS because of significant differences in the emissions intensities of the different types of generators. By 2035, the costs in the one-benchmark case are 34 percent lower than in the four-benchmark case.

Figure 10. Economic Cost as Function of Number (and Variation) of Benchmarks



Using multiple benchmarks can serve distributional objectives, however. Table G1 in Appendix G offers, for each province and in three cases differing by number and variation of benchmarks, the TPS's impact on incomes over the 2020-2035 interval. The differences in provincial impacts derive from significant differences in average carbon intensities of production. As expected, the percentage losses of income are much more unevenly distributed in the one-benchmark case than in the four-benchmark case, which provides less stringent benchmarks to provinces especially reliant on high-carbon-intensity electricity generation under business as usual. In the one-benchmark case, the difference in the income percentage change between the best-off and worst-off province is 2.4, higher than the difference (1.7) in the four-benchmark case. The standard deviation of percentage losses across provinces in the one-benchmark case is 0.502, 69 percent higher than in the four-benchmark case (0.297). These results reveal a significant trade-off between cost-effectiveness and distributional equity (and associated political acceptability) in the choice of TPS design.

In Appendix H, we consider further how the TPS's impacts on prices, costs, and emissions change under alternative policy designs and assumed parameter values. Our main findings are robust to changes in input substitution elasticities, capital transformation (mobility) elasticities, and assumed rates of increase in policy stringency.

7. Conclusions

China's recently implemented nationwide CO_2 tradable performance standard has the potential to contribute importantly to global reductions in CO_2 emissions. This paper assesses the TPS's potential costs and benefits over the interval 2020-2035, both in the aggregate and across sectors and provinces, and identifies the relative attractions and limitations of alternative specific policy designs.

Our analysis differs from earlier treatments because of its general equilibrium framework; attention to changes in impacts over time; recognition of differences between the TPS and C&T in structure, incentives, and impacts; recognition of the institutional and regulatory features of China's economy; and ability to consider a range of potential future TPS designs. The latter include alternative specifications for the variation and stringency of government-specified benchmarks and an allowance auction as a possible supplementary source of allowance supply.

The analysis yields several unique insights. First, we find that under plausible parameters and levels of policy stringency, the TPS's environmental benefits are well above its economic costs. Our central estimate is that the benefits exceed costs by a factor of more than five when only the climate benefits are considered and by a much higher factor when health benefits from reduced emissions of local pollutants are also considered.

Second, the stringency of the TPS as currently planned is considerably weaker than the efficiency-maximizing level. Based on assessments of marginal environmental benefits and economic costs, we find that efficiency maximization would require using benchmarks approximately 9–12 percent tighter than the current and projected benchmarks for 2020–2035.

Third, the relative cost of the TPS and an equivalently stringent C&T system depends importantly on system stringency and pre-existing taxes. Earlier literature had identified a cost-effectiveness handicap of the TPS relative to C&T because of the TPS's implicit subsidy to output. We show that the subsidy also yields an offsetting benefit by limiting the increase in output prices and reducing the associated adverse "tax-interaction effect" under the TPS. Indeed, in the short run, when required emissions reductions are relatively modest, the cost per ton of abatement under the TPS is very close to that under C&T. The TPS's costs significantly differ from C&T's only in the longer run, when greater stringency and associated higher allowances prices augment the distortionary cost of the TPS's implicit subsidy.

Fourth, introducing an auction as a complementary source of allowance supply can lower the economic costs of China's emissions trading system by 30–43 percent relative to the no-auction case. Auctioning lowers costs because there is no implicit subsidy to allowances introduced via auction. A further cost advantage arises to the extent that the auction revenues finance cuts in pre-existing distortionary taxes.

Finally, the simulation results reveal important trade-offs between cost-effectiveness and distributional equity. Distributional concerns can be addressed via varying (customized) benchmarks, but greater benchmark variation sacrifices cost-effectiveness by widening the disparities in marginal costs of production. Employing a single benchmark for the electricity sector would lower costs by 34 percent relative to the four-benchmark system in place but increase the standard deviation of percentage income losses across provinces by more than 60 percent.

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Appendix A. Production Structure and Functional Forms

Table A.1 summarizes the notation used in this appendix.

Table A.1. Notation

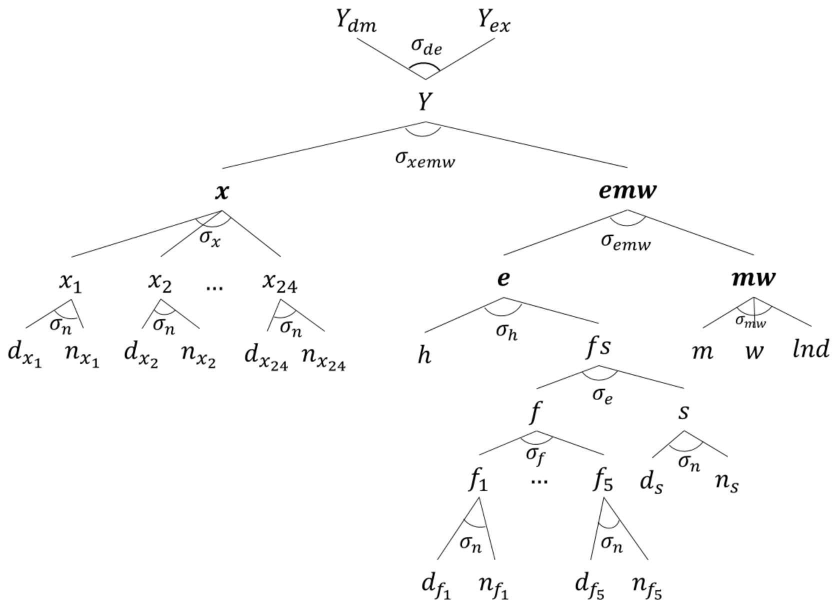
Symbol	Definition
Y	Output
R	Tax revenue
T	Lump-sum transfer
E	CO_2 emissions
p	Price of goods and factors
t	Price of allowances
x	Material inputs
e	Energy inputs (electricity and fuels)
s	Electricity inputs
f	Fuel inputs
d	Domestic intermediate inputs
n	Imported intermediate inputs
m	Labor inputs
w	Capital inputs
res	Natural resources inputs
lnd	Land inputs
$\overline{m}, \overline{w}, \overline{res}, \overline{lnd}$	Factor endowments
σ	The elasticity of substitution between inputs
α	Parameters of CES functions
i,j,l	Sectors
k	Subsectors

A.1. Production

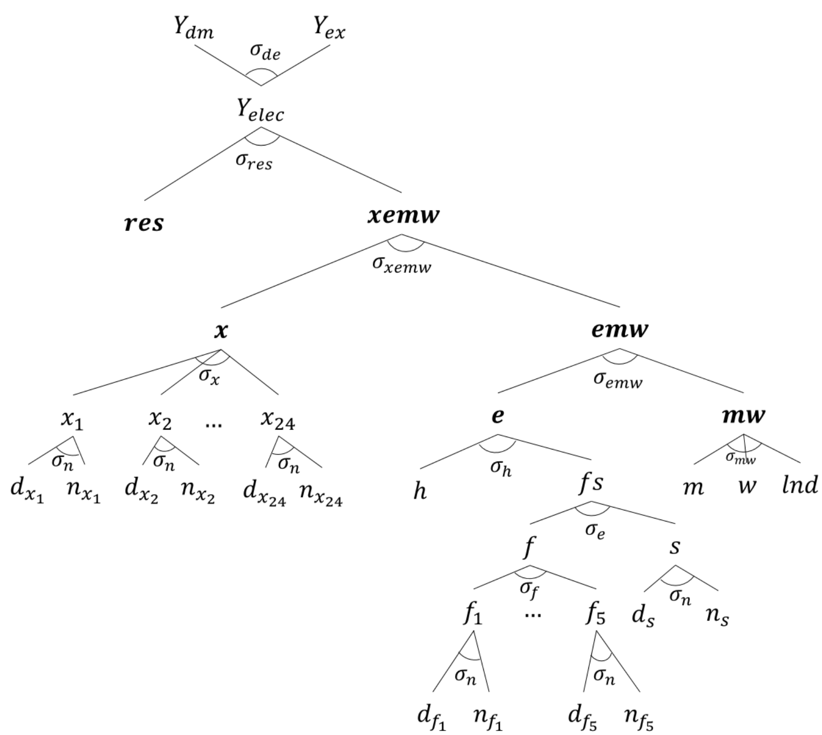
Production in each sector is represented by the nested structure shown in Figure A1; σ parameters are elasticities of substitution in production.

Figure A.1. Nested CES Production Structure for Each Sector

A. Fossil-fuel based electricity sector and other sectors



B. Solar, wind, hydro, and nuclear electricity subsectors



The structure described applies to all sectors other than electricity based on renewable energy resources and to subsectors of the electricity, iron and steel, and aluminum and cement sectors. The structures for solar, wind, hydro, and nuclear electricity subsectors are similar, except that they have natural resources (*res*) as their inputs.

In each sector or subsector, producers employ material inputs (*x*), energy inputs (*e*), and factors (*mw*) to produce output. As indicated in Figure A1, the material inputs x_1, x_2, ..., x_{24} combine to produce the composite material input *x*. Each x_i is a composite of a domestically produced material input $d_{x,i}$ and any foreign-produced material input $n_{x,i}$. The energy composite (*e*) is produced from electricity (*s*), heat (*h*), and fossil fuels (*f*), and the fossil fuel is a composite of five fuel inputs f_1, f_2, ..., f_5 (coal, crude oil, natural gas, gas manufacture and distribution, and petroleum). Producers also employ factors of production labor (*m*), capital (*w*), and any land (*lnd*). The output is *Y* allocated toward the domestic or export markets. Y_{dm} and Y_{ex} represent the output devoted to each of these markets.

The model employs the constant elasticity of substitution (CES) functional form for the production functions at each stage of the production nest. A general equation for it is

$$V = \left[\sum_{i=1}^{n} \alpha_i v_i^{\rho} \right]^{\frac{1}{\rho}}, \tag{A1}$$

where $\sum_{i=1}^{n} \alpha_i = 1$. The parameter ρ equals $1 - \frac{1}{\sigma}$, where σ is the elasticity of substitution among v_i in producing *V*. Equation A1 indicates the relationship, at any given point of the nest, between a given composite and its underlying elements. A constant elasticity of transformation (CET) function maps the total output Y into the domestic supply Y_{dm} and export Y_{ex}.

$$Y_{dm} = \alpha_{dm}^{\sigma_{de}} \left[\frac{p_{dm}}{p} \right]^{-\sigma_{de}} Y \tag{A2}$$

$$Y_{ex} = \alpha_{ex}^{\sigma_{de}} \left[\frac{p_{ex}}{p} \right]^{-\sigma_{de}} Y, \tag{A3}$$

where $\alpha_{dm} + \alpha_{ex} = 1$, and σ_{de} is the elasticity of transformation between Y_{dm} and Y_{ex}. p_{dm}, p_{ex} and p denote the domestic price, export price, and composite price of the produced good, respectively. As these functions indicate, the fraction of *Y* devoted to the domestic market and exports is a function of the real prices of goods sold to the domestic and foreign markets. In all equations in this appendix, the price shown is inclusive of any tax and net of any subsidy.

A.2. State-Owned Enterprises

State-owned enterprises (SOEs) and privately owned enterprises (POEs) are modeled as profit-maximizing firms that enjoy subsidies and face taxes. SOEs receive favorable treatment relative to POEs through input subsidies. Nevertheless, the two types of firms share the markets for specific products and receive the same prices for these products. For a given product, both SOEs and POEs choose levels of output that bring the marginal costs from their differing marginal cost functions up to the common output price.

SOEs benefit from preferential treatment through lower interest rates in capital markets due to government subsidies (Cull and Xu, 2003; Guariglia et al., 2011; Song et al., 2011; Harrison et al., 2019). These are modeled as subsidies to their capital inputs. SOEs also offer superior benefits to their employees, including higher social security and pensions. The associated higher labor costs are often offset by government transfers (Hering and Poncet, 2010; Démurger et al., 2012; Berkowitz et al., 2017). This is captured via a higher tax rate on the labor input of SOEs and lump-sum transfers from the government.

The model assumes two representative firms in each sector (or in each subsector, when subsectors are identified), with one each for SOEs and POEs.

A.3. Administered Electricity Pricing

In China's electricity markets, generators sell some of their electricity at a government-administered price and some at market prices. The market price applies at the margin, that is, for the supply beyond a government-specified quantity to which the administered price applies inframarginally. The data indicates that the government-administered price is higher (CEC, 2019). We assume that it will remain constant at the level in the data but the share of the administered electricity will decrease linearly to 0 before 2025, following the expectation that China's electricity market will be fully liberalized by 2025. Thus, the model incorporates administered pricing only through 2024.

A piecewise marginal revenue function captures the hybrid pricing structure. Three cases apply; Y_A is the level of output at which administered pricing no longer applies.

Case i) For firms that produce output above Y_A, the marginal cost is below the market price at the quantity Y_A, so firms have incentives to exceed Y_A and face the market price at the margin. Total consumer expenditure on electricity exceeds $p \cdot Y$: this total is $p \cdot Y + (p_A - p) \cdot Y_A$. The consumers effectively face a lump-sum tax of $(p_A - p) \cdot Y_A$.

Case ii) For firms that would produce less than Y_A, the marginal cost at the level Y_A is higher than the administered price p_A. The profit-maximizing output level is $Y < Y_A$. All electricity is sold at the price p_A.

Case iii) For firms that would produce Y_A, the marginal cost at the level Y_A is lower than or equal to the administered price p_A but higher than the market price p. These firms could earn rents if p_A exceeds their marginal cost, yet they have no incentive to exceed Y_A, because output beyond Y_A would need to be sold at the market price p, which is below marginal cost.

A.4. Factor Types and Supply

Labor (*m*) is perfectly mobile across sectors, capital (*w*) is imperfectly mobile, and land (*lnd*) and natural resources (*res*) are immobile. In all sectors and in each period, the supplies of the imperfectly mobile factor are captured via a transformation function that allocates capital across sectors and subsectors. Changes in relative prices alter this allocation. The marginal returns to capital and associated market price of capital generally will differ across sectors and subsectors, a reflection of imperfect mobility.

The transformation function, $\Gamma_{w_i}(\square)$, has the CET functional form and is expressed by

$$\overline{w} = \left[\sum_{j=1}^{31} \alpha_{w,j} w_j^{S\rho_w}\right]^{1/\rho_w}; \tag{A4}$$

$\sum_{j=1}^{31} \alpha_{w,j} = 1$, and $\rho_w = 1 - \dfrac{1}{\sigma_w}$, where σ_w is the elasticity of transformation among sectors. The element $\overline{w}$ denotes the fixed endowment of capital and w_j^S the allocation of $\overline{w}$ to sector *j*.

The model assumes that owners of capital make investments so as to maximize their returns from capital. The maximization problem is expressed by the following:

$$\max_{w_j^S} \sum_{j=1}^{j=31} w_j^S P_{wj}$$
$$s.t.\quad \Gamma_w\left(w_{\mathrm{j}}^{\mathrm{S}}\right) = \overline{w} \qquad (A5)$$

where w_j^S denotes the allocation of capital to sector *j* and p_{wj} is the sector-specific price of the factor *w*. $\Gamma_{w_i}(\square)$ is the CET function for capital. As indicated, the model distinguishes subsectors of the electricity, cement, aluminum, and iron and steel sectors, to reflect within-sector differences in technology or emissions intensities. The same maximization problem determines the allocation of capital across subsectors.

The government's preferential treatment of SOEs (described) influences both the average return to capital and its relative returns across sectors. These interventions affect the capital owner's optimizing investment decisions and the allocation of capital across sectors. The same maximization problem in Equation A5 determines the allocation of capital between SOEs and POEs within a subsector.

A.5. Inputs and Outputs

Firms make choices of variable inputs and levels of output consistent with the objective of profit maximization. The modeling of these choices is shown next; for convenience, the sector subscript is suppressed.

A.5.1. Optimal Input Intensities

For any CES function of the form in Equation A1, the Lagrangian equation for obtaining the composite V at minimum cost is given by

$$L = \sum_{i=1}^{n} p_i v_i + \lambda \left\{ \left[\sum_{i=1}^{N} \alpha_i v_i^{\rho} \right]^{\frac{1}{\rho}} - V \right\}, \qquad (A6)$$

where p_i is the price of input v_i. From this minimization problem, the optimal demand of input v_i per unit of the composite *V* is derived as

$$\frac{v_i}{V} = \alpha_i^{\sigma} \left[\frac{p_i}{p} \right]^{-\sigma}, \qquad (A7)$$

where σ is the CES equal to $\dfrac{1}{1-\rho}$ and *p* is the price of the composite *V*:

$$p = \left[\sum_{i=1}^{n} \alpha_i^{\sigma} p_i^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \qquad (A8)$$

A.5.2. Optimal Supply of Output

or fossil-based electricity subsectors and other sectors, the profit function is

$$\begin{aligned}\Pi &= pY - C \\ &= pY - p_{\boldsymbol{x}}x - p_{\boldsymbol{emw}}emw\end{aligned} \quad \text{(A9)}$$

For the solar, wind, hydroelectricity, and nuclear subsectors, the profit function is

$$\Pi_k = pY - p_x x - p_{emw}emw - p_{rk}res_k \ , \quad \text{(A10)}$$

where the *C* is the cost of production inputs, which equals the payment to ***x*** and ***emw***, and p_{rk} res_k denotes the price and endowment for natural resources. The *p* denotes the composite price of the produced good:

$$p = \left[\alpha_{dm}^{\sigma_{de}} p_{dm}^{1-\sigma_{de}} + \alpha_{ex}^{\sigma_{de}} p_{ex}^{1-\sigma_{de}} \right]^{\frac{1}{1-\sigma_{de}}} \ , \quad \text{(A11)}$$

where p_{dm} is the domestic price, p_{ex} the export price, and σ_{de} the elasticity of transformation between domestic and export supply. Thus, the composite price is a function of the market prices for the sale of the output to the domestic and export markets.

Differentiating the profit function with respect to ***x*** gives the first-order condition for ***x***, where the left-hand and right-hand sides represent the marginal revenue and cost of ***x***, respectively:

$$p\frac{\partial Y}{\partial \boldsymbol{x}} = p_{\boldsymbol{x}} \, . \quad \text{(A12)}$$

From the first-order condition, we can solve the optimal quantity of ***x*** as a function of output.

$$\boldsymbol{x} = \alpha_{\boldsymbol{x}}^{\sigma_{xemw}} \left[\frac{p_{\boldsymbol{x}}}{p} \right]^{-\sigma_{xemw}} Y \, . \quad \text{(A13)}$$

Similarly, differentiating the profit function with respect to ***emw*** gives the first-order condition for ***emw***. From that, we have the optimal quantity of ***emw*** as a function of output.

$$p\frac{\partial Y}{\partial \boldsymbol{emw}} = p_{\boldsymbol{emw}} \quad \text{(A14)}$$

$$emw = \alpha_{emw}^{\sigma_{xemw}} \left[\frac{p_{emw}}{p} \right]^{-\sigma_{xemw}} Y. \quad \text{(A15)}$$

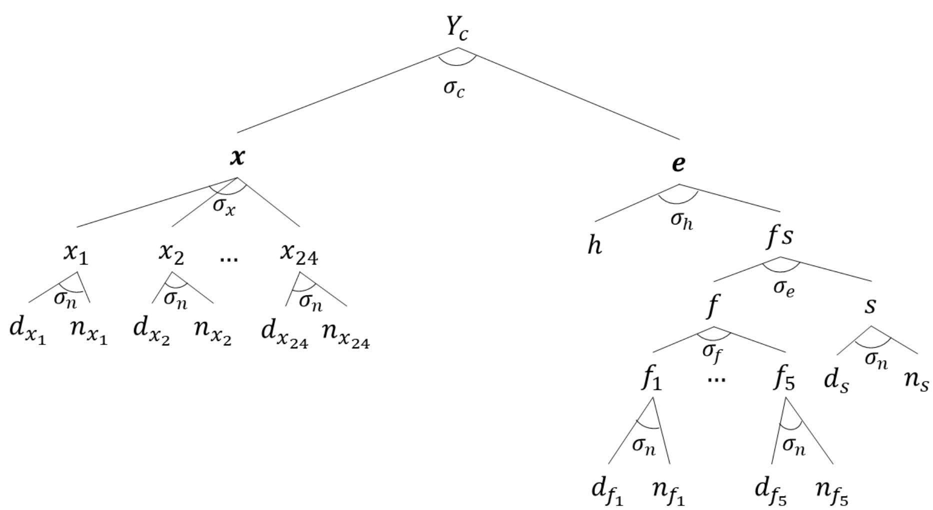
Under the model's production structure, each firm's production exhibits constant returns to scale. The firm chooses the level of output at which the marginal production cost equals the price. Applying the optimal ***x*** and optimal ***emw*** in Equations A13 and A15 to the optimal input intensities, we get the optimal levels of all inputs.

A.6. Household Behavior

A.6.1. Consumption

In the model, a representative household makes consumption choices to maximize utility. Figure A2 shows the nested structure of the utility function. The household chooses between material goods (***x***) and energy goods (***e***). At the next level, the material composite is a CES combination of material goods, $x_1, x_2, \ldots, x_{24}$. The energy composite is a CES function of electricity (*s*), heat (*h*), and fuel composite (*f*). The latter is a CES function of five fuel goods, $f_1, f_2, \ldots, f_5$. Each x_l, f_l, and *s* is a composite based on the domestic and foreign component.

Figure A.2. Household Demand Structure



The CES functional form in Equation A1 applies to all nests in the household demand structure. The form of the price function in Equation A8 applies to the composite prices for all nests of the household demand structure. The household maximizes utility subject to its budget constraint. The maximization problem is

$$\max U\left(Y_C\right) = Y_C$$
$$s.t. \quad p_C Y_C \leq p_m \overline{m} + p_w \overline{w} + p_{res} \overline{res} + p_{lnd} \overline{lnd} + T - S, \qquad \text{(A16)}$$

where

$p_C Y_C$ is the household expenditure,

$p_m \overline{m}$ is income from the endowments of labor,

$p_w \overline{w}$ is income from the endowments of capital,

$p_{res} \overline{res}$ is income from the endowments of natural resources,

$p_{lnd} \overline{lnd}$ is income from the endowments of land,

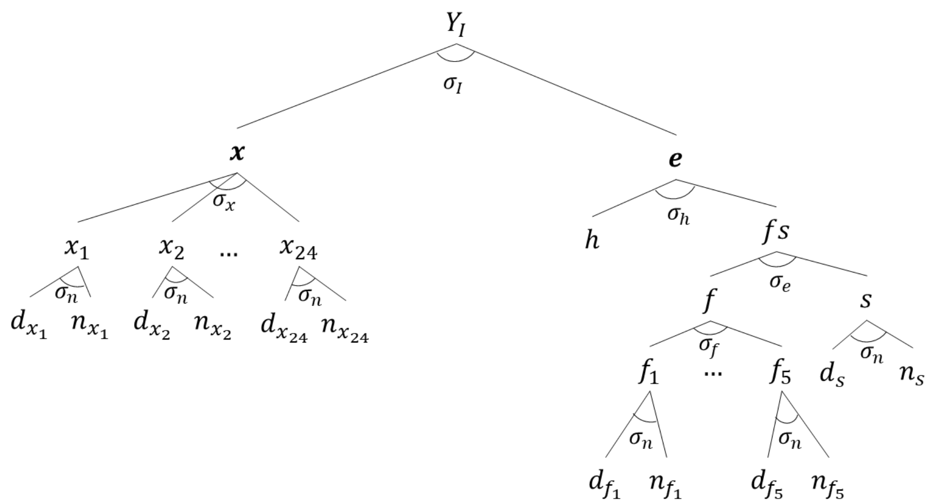
T is the transfer from the government, and

S is private saving (discussed later).

A.6.2. Investment

Production of the investment involves the CES nested structure in Figure A3.

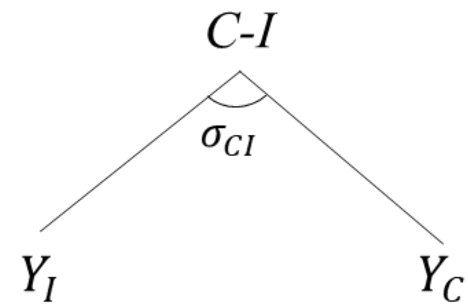
Figure A.3. Nested Structure for Investment



The generalizable CES function form in Equation A1 applies to all nests in the investment good production structure. The investment good is produced at the minimum cost. The minimum cost problem has the same form as that of the cost-minimization problem of commodity goods, so the generalizable form in Equation A8 applies to the investment good.

Households spend money on consumption and investment. The expenditure on the investment good is determined by its price and the substitution elasticity between consumption and investment (see Figure A4).

Figure A.4. Structure for Households' Investment and Consumption Decisions



Households' expenditure on investment represents private saving. Therefore, following Paltsev (2005), household investment is determined by

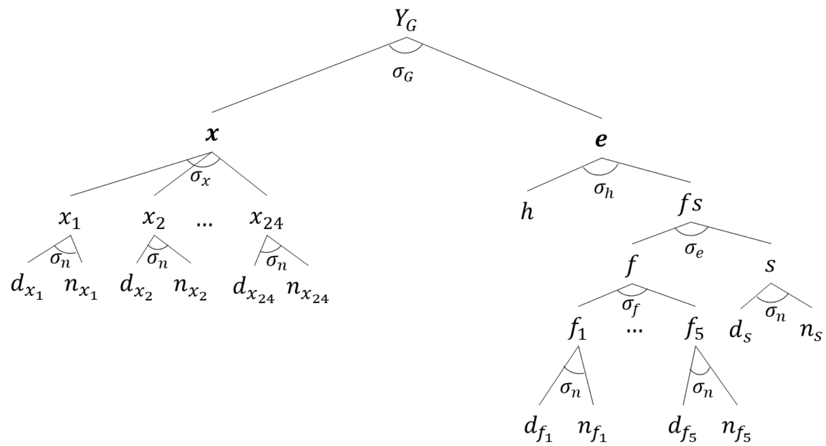
$$\frac{\frac{S_t}{INC_t} - \frac{S_0}{INC_0}}{\frac{S_0}{INC_0}} = -\varepsilon_I \frac{\frac{p_{I,t}}{p_{C-I,t}} - \frac{p_{I,0}}{p_{C-I,0}}}{\frac{p_{I,0}}{p_{C-I,0}}} - t \cdot exr\,, \tag{A17}$$

where S_t represents private saving and INC_t households' total income. The left-hand side represents the change in private saving rate relative to the benchmark data. $p_{I,t}$ is the cost of investment good in period *t,* determined by Figure A4. $p_{C-I,t}$ is the price of a consumption-investment composite. S_0, INC_0, $p_{I,0}$, and $p_{C-I,0}$ represent them in the benchmark data. The ε_I is the elasticity between private saving rate and the price of investment good relative to the consumption-investment composite, $\varepsilon_I = -\sigma_{CI}(1 - \frac{S_0}{INC_0})$, and *exr* is the annual reduction rate that represents an exogenously decreasing trend of private saving rates in China.

A.7. Government Behavior

Government spending in the model is characterized by a CES preference function defined over a material-energy composite. The structure is the same as that for household consumption, with the only difference being the elasticity values and the shares of the inputs.

Figure A.5. Nested Structure for Government Spending



The government is assumed to balance its budget each year:

$$p_G Y_G = R - T - I_G \,, \tag{A18}$$

where $p_G Y_G$ is the expenditure on public consumption, *R* the total tax revenue (consists of output taxes, intermediate demand taxes, factor taxes, and final demand taxes), *T* the transfers to households, and I_G the public saving. Government consumption is set as a fixed share of GDP and characterized by a CES preference function defined over the material-energy composite. The transfer to households is endogenously determined by the government's budget balance requirement. Public saving is also specified as a fixed share of GDP.

The generalizable CES function form in Equation A1 applies to all nests in the government demand structure. The composite final good is produced at minimum cost. The minimum cost problem has the same form as that of the cost-minimization problem for the outputs of the model's various sectors, so the generalizable form in Equation A8 applies to the government's composite good.

Appendix B. Data and Method for Subsector Classification and Data Processing

B.1. Subsector Classification

In the model, the electricity, cement, aluminum, and iron and steel sectors include subsectors distinguished by technology or emissions intensity.

B.1.1. Electricity Sector

The electricity sector embraces 15 subsectors, with each representing a different generation technology. The first 11 technologies differ in terms of fuel input (coal or gas), capacity (300MW, 600MW, etc.), and temperature and pressure (subcritical, supercritical, etc.). The 12th–15th technologies are low-carbon (wind, solar, hydro, and nuclear) electricity generation. The differing fuel input intensities imply different emissions intensities.

Table B.1. Subsectors of the Electricity Sector

Technology Category	Subsector
Coal-fired (other than circulating fluidized bed)	LUSC: 1000MW Ultra-supercritical
	SUSC: 600MW Ultra-supercritical
	LSC: 600MW Supercritical
	SSC: 300MW Supercritical
	LSUB: 600MW Subcritical
	SSUB: 300MW Subcritical
	OTHC: Install capacity less than 300MW
Circulating fluidized bed	LCFB: Circulating Fluidized Bed Units (with installed capacity greater than or equal to 300MW)
	SCFB: Circulating Fluidized Bed Units (with installed capacity less than 300MW)
Gas-fired	HPG: F-class
	LPG: Pressure lower than F-class
Other	Wind power
	Solar power
	Hydropower
	Nuclear power

Our data contain 1,929 coal-fired and gas-fired units, generating 23 billion kWh in 2017, covering 49.7 percent of coal- and gas-fired generation.[51]

The cement and aluminum sectors include subsectors categorized according to their observed emissions intensities. The iron and steel sector includes subsectors categorized by their production technologies and observed emissions intensities. We use a machine-learning method to cluster plants with varying emissions intensities into subsectors. The first step is to decide the number of subsectors. The second step is to employ the clustering algorithm to find cluster centers and assign plants to each cluster such that the distance (the difference between the center's and plant's emissions intensities) is minimized. Algorithms differ in how "cluster center" and "distance" are defined. We employ the k-means algorithm. Next, we document this clustering process for cement, aluminum, and iron and steel.

B.1.2. Cement

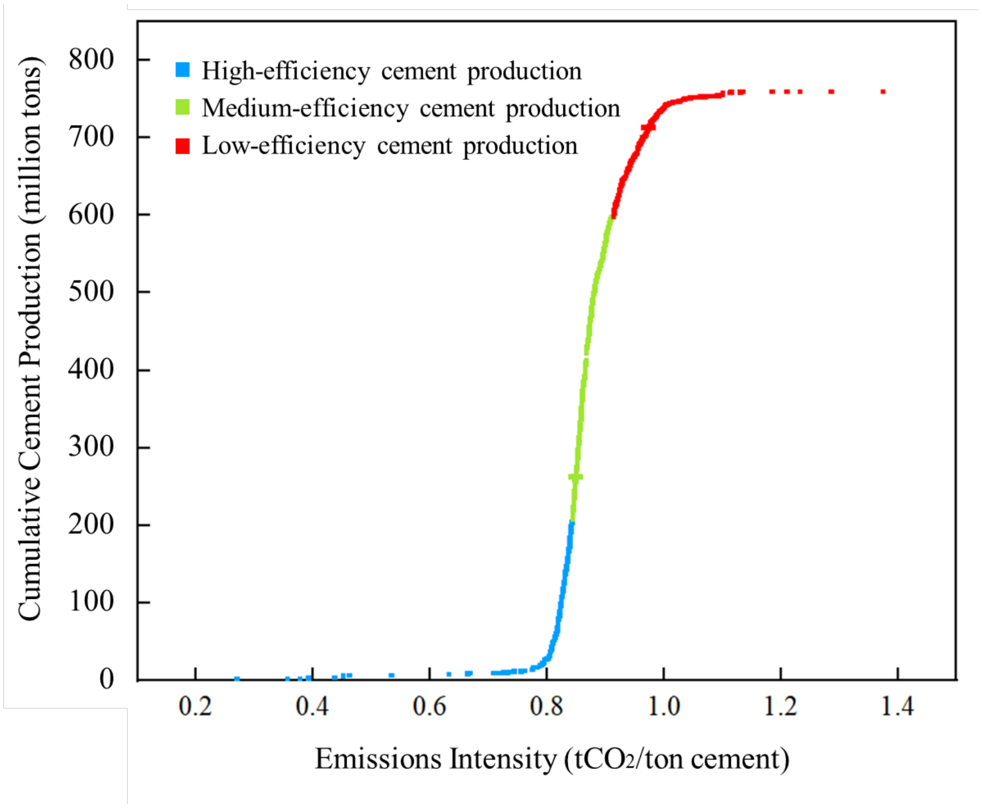
Our data contain 797 production facilities from 631 cement firms, covering 57 percent of production.[52] We have the CO_2 emissions intensity data for each facility.[53] We apply a clustering algorithm to group the production facilities into five clusters. The lowest and highest clusters have very few facilities, so we include them in the closest intermediate groups. Each of the resulting three clusters represents a subsector (see Table B2). Figure B1 shows the cumulative density function that captures the relationship between the emissions intensities of the three emissions-intensity groups and cumulative cement production.

Table B2. Subsectors of the Cement Sector

Subsector	CO_2 emissions intensity
High efficiency	CO_2 emissions intensity < 0.845 tCO_2/ton cement
Medium efficiency	0.914 > CO_2 emissions intensity ⩾ 0.845 tCO_2/ton cement
Low efficiency	CO_2 emissions intensity ⩾ 0.914 tCO_2/ton cement

[51] The data were collected on a voluntary basis by the Ministry of Ecology and Environment (MEE), leading to some missing data. However, we believe the available data to be representative. The average emissions intensity of fossil-based electricity production in our dataset is 0.78 tCO_2/MWh. This closely aligns with the national average for the corresponding year (0.77 tCO_2/MWh in the Energy Balance Table of 2017).
[52] The average emissions intensity of cement in our data is 0.87 tCO_2/ton. This value closely aligns with the published national average of 0.87 tCO_2/ton (Ding, 2021), making the dataset representative.
[53] The cement production process is primarily divided into two steps: cement clinking and clinker grinding. The emissions data are from clinking. Given that the emissions from the second step account for a minor fraction of the total emissions, using the emissions intensity of clinking to define subsectors approximates fairly closely the production emissions intensity.

Figure B1. Clustering of Cement Sector by Emissions Identity



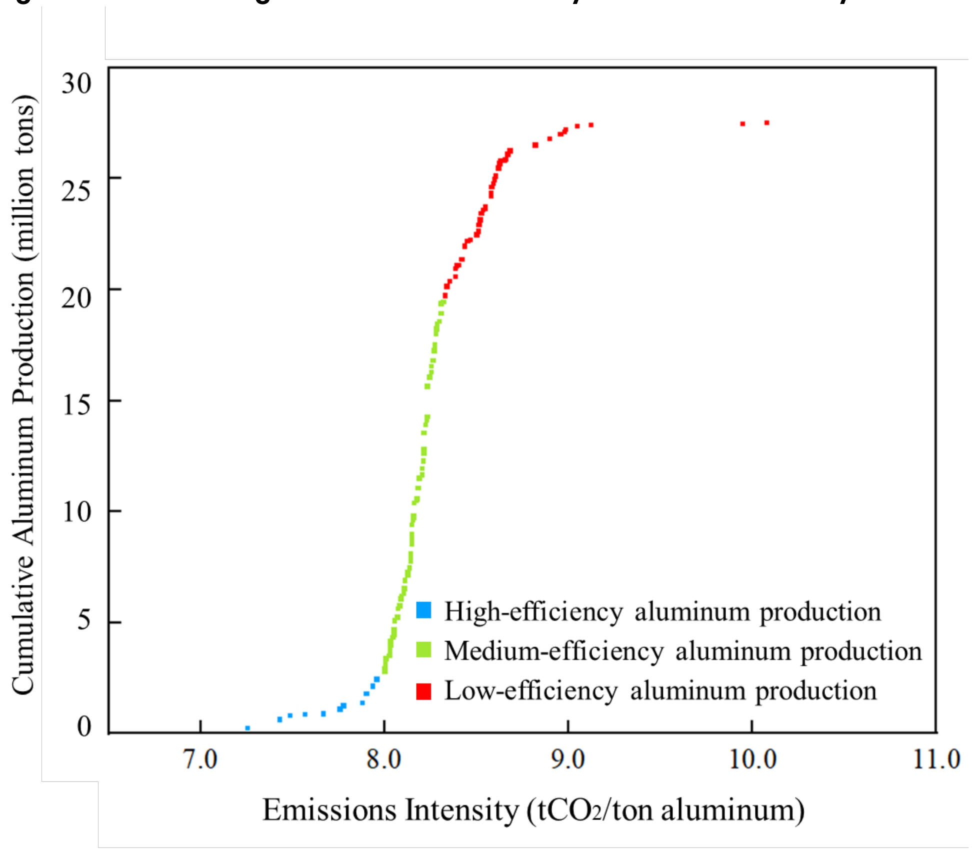
B.1.3. Aluminum

Our data contain 116 production facilities from 64 aluminum firms, covering 42 percent of production. We use the same clustering method as cement—we first group the 116 production facilities into five clusters and regroup the lowest and highest clusters to their closest groups. We end up with three clusters, each representing one subsector in the aluminum sector (see Table B3 and Figure B2).

Table B3. Subsectors of the Aluminum Sector

Subsector	CO_2 emissions intensity
High efficiency	CO_2 emissions intensity < 8.00 tCO_2/ ton aluminum
Medium efficiency	8.33 > CO_2 emissions intensity ≥ 8.00 tCO_2/ ton aluminum
Low efficiency	CO_2 emissions intensity ≥ 8.33 tCO_2/ ton aluminum

Figure B2. Clustering of Aluminum Sector by Emissions Intensity



B.1.4. Iron and Steel

We first classify iron and steel units into two technology categories: basic oxygen (BO) and electric arc (EA) furnace steelmaking. Units within each category are classified into subcategories based on their observed emissions intensities.

China has 187 BO steelmaking units with a total production of 600 million tons of crude steel and 262 EA steelmaking units with a total production of 133 million tons of crude steel. In total, our data cover 88 percent of production in 2017.[54]

We use the same clustering method as that for cement and aluminum. We organize the 187 BO and 259 EA steelmaking units into five clusters for each sector and regroup the lowest and highest ones into their closest groups. We end up with three clusters per sector, each representing one subsector.

Table B4. Subsectors of the Iron and Steel Sector

Subsector	CO_2 emissions intensity
Basic oxygen steelmaking	CO_2 emissions intensity < 1.41 (tCO_2/ton)
	1.98 > CO_2 emissions intensity ⩾ 1.41 (tCO_2/ton)
	Carbon emissions intensity ⩾ 1.98 (tCO_2/ton)
Electric arc furnace steelmaking	CO_2 emissions intensity < 0.125 (tCO_2/ton)
	0.235 > CO_2 emissions intensity ⩾ 0.125 (tCO_2/ton)
	CO_2 emissions intensity ⩾ 0.235 (tCO_2/ton)

[54] The average emissions intensity of BO and EA iron and steel production in our data is 1.40 tCO_2/ton, which closely aligns with the published national average level of 1.37 tCO_2/ton (NBS, 2018).

Figure B3. Clustering of Electric Arc Furnace Steelmaking by Emissions Intensity

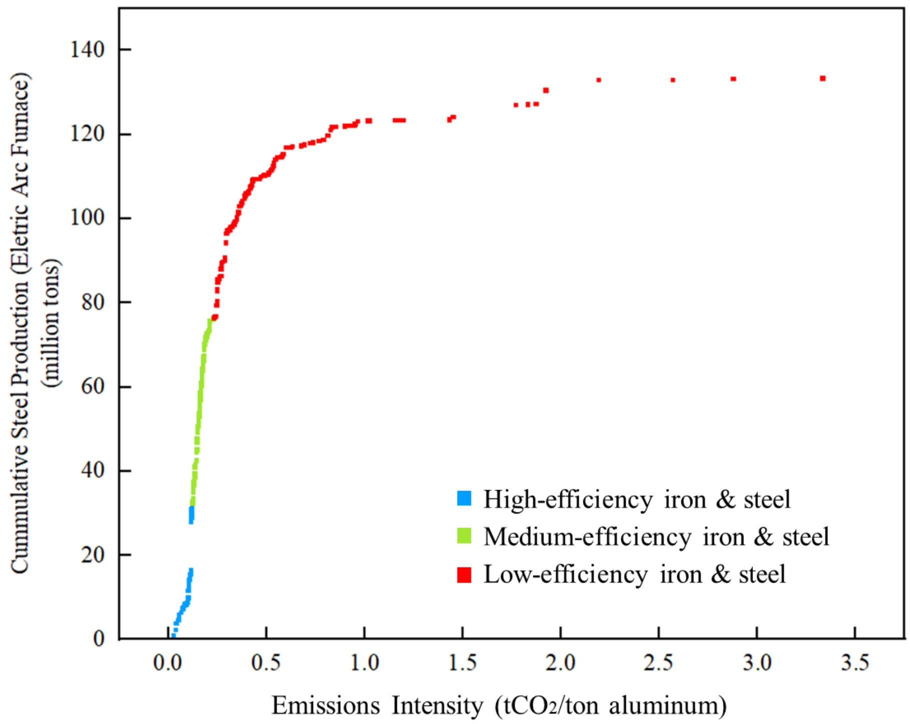
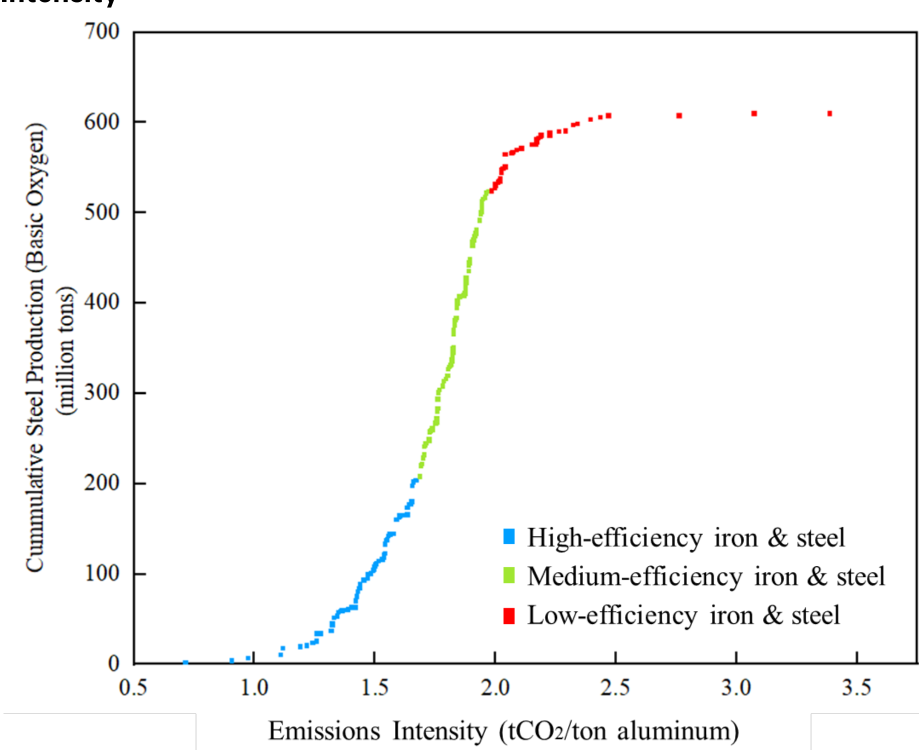


Figure B4. Clustering of Basic Oxygen Steelmaking by Emissions Intensity



B.2. Data Processing

The data are processed in four steps. First, the 149 sectors' input-output data from China's 2017 input-output table are aggregated to the 31 production sectors in our study and scaled to 2020, the first simulation year. We use three scalers to translate these data to 2020: for the service, agriculture, and other sectors. The data are scaled so that the GDP and the value-added shares of the service and agriculture sectors match the published statistics in 2020 (NBS, 2021). Second, we disaggregate the sectors into subsectors for electricity, cement, aluminum, and iron and steel according to the subsector-level information (see next paragraph), which is obtained by aggregating the firm-level Ministry of Ecology and Environment (MEE) data. Third, we scale all tax and subsidy rates reported in GTAP for 2014 (the latest version) by a common factor so that the total tax revenue net of subsidies matches that in 2020 (NBS, 2021).[55] Fourth, we rebalance the input-output data after these adjustments, as described in the subsection "Input-Output Table Rebalance." Last, we further disaggregate the sectors (or subsectors for electricity, cement, aluminum, and iron and steel) into SOEs and POEs, which ensures that the inputs and outputs of SOEs and POEs match the empirical evidence while maintaining the balance of the input-output data. Appendix C provides details about the parameters related to SOEs and POEs.

B.2.1. Disaggregating Sector-Level Data to the Subsector Level

The input-output table provides sector-level data on economic values. The sectors are then split into subsectors (for electricity, cement, aluminum, and iron and steel sectors).

For factor inputs (m_j, w_j), material inputs d, n, and exports (Y_{ex}), sector-level electricity, cement, and aluminum data are split into subsectors by assuming that each subsector's share of a corresponding input (or export) equals its output share. As for the material inputs for the iron and steel sector, we consider the different technical properties of the BO and EA furnace steelmaking subsectors: BO steelmaking converts iron ore into pig iron and then into steel, whereas EA steelmaking directly converts scrap or direct reduced iron to steel. Therefore, we assume that the BO steelmaking subsector uses all the iron ore and mineral material inputs in the iron and steel sector. The iron and steel inputs of the EA steelmaking subsector account for 60 percent of its total input; those inputs of the BO steelmaking subsector only account

[55] Wind and solar have higher unit cost than fossil-based electricity. China's government gives subsidies to solar and wind electricity generators. We obtain the subsidy rates from Direct Trading Pilots of Green Power. The subsidies are projected to decrease to 0 before 2025 (Tu et al., 2019; Zhang et al., 2021). Therefore, we assume that the subsidy rates for wind and solar electricity will decrease linearly to zero in 2025.

for 20 percent, according to Lu et al. (2015). Other material inputs, factor inputs, and exports are split in the same way as the electricity, cement, and aluminum sectors.

For energy inputs in the electricity sector, the MEE data provide each coal(gas)-fired subsector's share of coal (gas) use. For energy inputs in the cement and the iron and steel sectors, the MEE data provides each subsector's share of fuel composite, which we assume applies to each fuel. For energy inputs in the aluminum sector, the MEE data provide each subsector's share of electricity input; we assume that it also applies to other energy inputs.

The MEE data provide emission data in electricity, cement, aluminum, and iron and steel sectors that only cover a subset of the whole sector. For example, data on the cement sector cover 57 percent of China's production. We scale the emissions data up by the share of coverage for each of the four sectors. Then, for the electricity, cement, aluminum, and iron and steel sectors, the emission data at the sector level are split into subsectors in the same way as we split energy inputs. The cement sector, in addition to emissions from energy inputs, also emits CO_2 during carbonate decomposition ($CaCO_3$ decomposed to CaO and CO_2).

B.2.2. Input-Output Table Rebalance

After data processing, the original input-output table is unbalanced—the total inputs of a sector differ from its total outputs. We thus apply a least-square optimization method to obtain a balanced table following Zhang et al. (2013):

$$
\begin{aligned}
&\min_{\{d_{x_{ijk}}, e_{ljk}, w_{jk}, m_{jk}\}} \sum_{i,j,k} \{(d_{x_{ijk}} - \overline{d_{x_{jik}}})^2 + (w_{jk} - \overline{w_{jk}})^2 + (m_{jk} - \overline{m_{jk}})^2 + (e_{jk} - \overline{e_{jk}})^2\} \\
&s.t. \\
&\sum_i (d_{x_{ijk}} + w_{jk} + m_{jk} + e_{ljk}) \cdot (1 + \overline{\theta_{res_{jk}}}) = (\sum_k Y_{dm_{jk}} + \sum_k \overline{Y_{ex_{jk}}}) \cdot \psi_{jk}, \forall j,k \\
&\sum_{i,k} d_{x_{jik}} \equiv \sum_k Y_{dm_{jk}} \\
&d_{x_{jik}}, w_{jk}, m_{jk}, e_{ljk} > 0, \\
&d_{x_{jik}} \equiv 0, \forall \overline{d_{x_{jik}}} = 0 \\
&w_{jk} \equiv 0, \forall \overline{w_{jk}} = 0 \\
&m_{jk} \equiv 0, \forall \overline{m_{jk}} = 0 \\
&e_{ljk} \equiv 0, \forall \overline{e_{ljk}} = 0,
\end{aligned}
\tag{A19}
$$

where $d_{x_{ijk}}$ represent the adjusted domestic material input *i* of sector *j*, subsector *k*, e_{ljk} the energy input *l*, w_{jk} the capital input, and m_{jk} the labor input. $\overline{d}_{x_{ijk}}$, $\overline{e}_{ljk}$, $\overline{w}_{jk}$, $\overline{m}_{jk}$ represent the corresponding accounts before the rebalance. $\theta_{res_{jk}}$ is the share of natural resources for low-carbon electricity production subsectors. The objective function minimizes the difference between the adjusted and unadjusted original value. In the first constraint, the left-hand side represents the total inputs of sector *j*, subsector *k*. The right-hand side is the total output of sector *j*, subsector *k*, where ψ_{jk} represents the subsector *k*'s output share in sector *j*.

B.3. Data on Import and Export and Emissions Intensity by Sector

Table B5. Import and Export as Ratios to Sectors' Total Output

Sector	Export to total output (%)	Import to total output (%)
Cement	0	0
Iron and steel	5	4
Aluminum	8	1
Pulp and paper	4	6
Other nonmetal products	5	2
Other nonferrous metals	3	14
Raw chemicals	7	14
Agriculture	1	7
Mining	1	63
Food	3	4
Textile	16	5
Clothing	36	4
Log and furniture	19	4
Printing and stationery	25	3
Daily chemical products	9	7
Metal products	12	4

General equipment	16	16
Transport equipment	7	17
Electronic equipment	36	22
Other manufacturing	11	27
Water	0	0
Construction	0	0
Transport	14	6
Services	4	3
Electricity	0	0
Petroleum refining	2	5
Heat	0	0
Coal	1	12
Crude oil	1	238
Natural gas	0	0

Table B6. Sector Emissions Intensities

Sector	Emissions intensity (t/*k*RMB)
Cement[*]	1.944
Iron and steel	0.235
Aluminum	0.446
Pulp and paper	0.053
Other nonmetal products	0.062
Other nonferrous metals	0.054
Raw chemicals	0.098
Agriculture	0.013

Mining	0.018
Food	0.008
Textile	0.007
Clothing	0.002
Log and furniture	0.003
Printing and stationery	0.001
Daily chemical products	0.003
Metal products	0.003
General equipment	0.005
Transport equipment	0.002
Electronic equipment	0.001
Other manufacturing	0.004
Water	0.038
Construction	0.003
Transport	0.072
Services	0.001
Electricity	0.858
Petroleum refining	0.041
Heat	0.756
Coal	0.029
Crude oil	0.043
Natural gas	0.007
Gas manufacture and distribution	0.003

*Cement has a higher emissions intensity in value terms than that of electricity. However, it is not covered by the TPS until the second phase, so its benchmarks are relatively less stringent than those of electricity; it also has a lower demand elasticity. Therefore, in Section 6.2, the output quantity reduction is less significant than that of electricity.

Appendix C. Parameters and Calibration Methods

C.1. Production Parameters

The balanced input-output table described in Appendix B provides benchmark data for output, material, energy and factor inputs. We then calibrate the share parameters of CES functions that have the functional form of Equation A1, α_i , by inverting the optimal input intensity function, Equation A7:

$$\alpha_i = (\frac{v_i}{V})^{1/\sigma} \cdot \frac{p_i}{p}, \tag{A20}$$

where α_i is the share parameter of the CES production function, V the output quantity, v_i the quantity of input *i*, p_i the benchmark price of input *I*, and p the benchmark price of output.

To calibrate α_i , we need to obtain the elasticities of substitution (σ) at different levels of the nested CES structure. In the next subsections, we discuss how we obtain them.

C.1.1. Substitution Elasticity Between Electricity and Other Fuels (σ_e)

One important parameter is the elasticity of substitution between electricity and other fuels (σ_e). We calibrate this based on data for the price elasticity of demand for electricity; estimates in China range from -0.1 (Shi et al., 2012) to -2.9 (He and Reiner, 2016), with most of the long-run values (consistent with the scope of our model) around -0.5. We adopted the -0.5 estimation by Hu et al. (2019) due to its more recent and rich dataset.

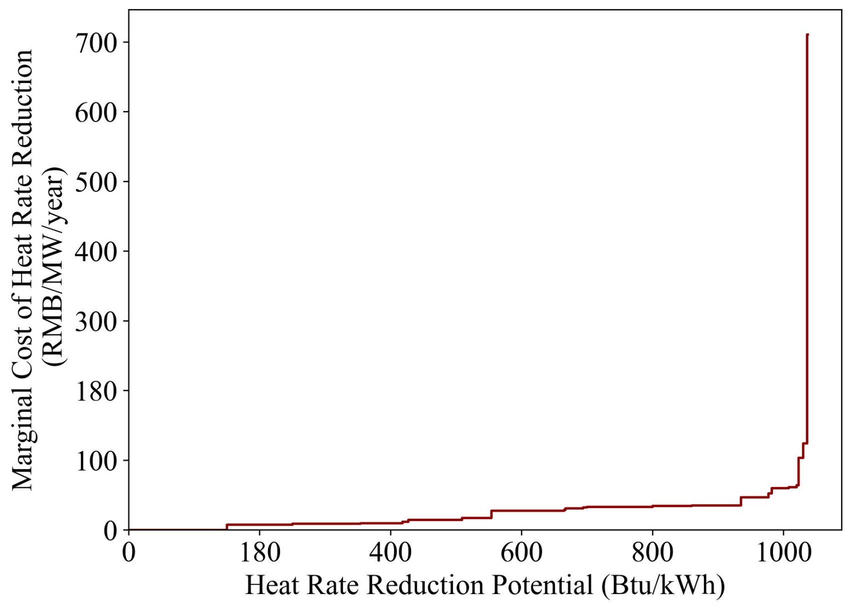
C.1.2. Substitution Elasticity Between the Energy Composite and Factor Composite (σ_{emw})

Our aim is to estimate the ease of changing the heat rate for each of the fossil-based electricity subsectors. Heat rate, which measures the energy used by a power plant to generate one kilowatt-hour (kWh) of electricity, serves as an efficiency indicator for power plants.

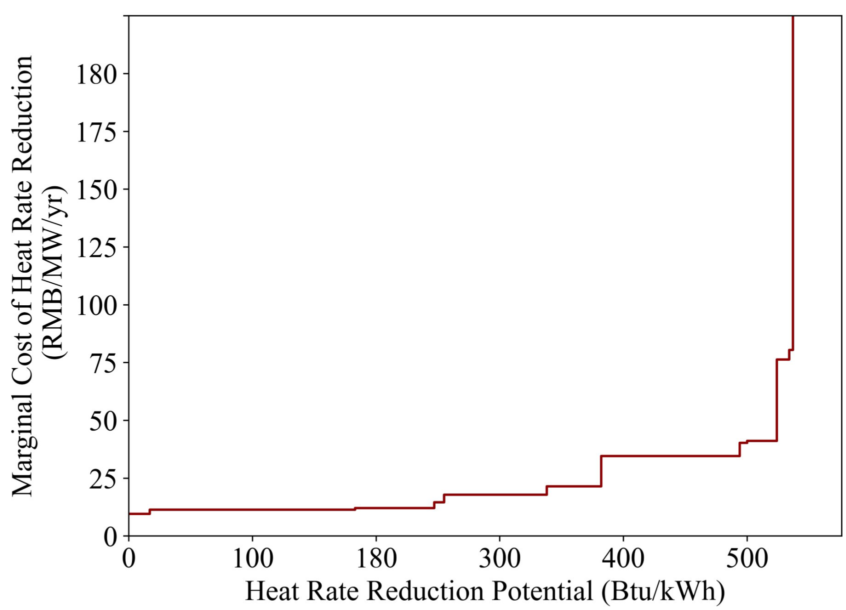
The NDRC reports (NDRC, 2016, 2017) provide estimates on the costs and potential heat rate reductions across different measures for both coal-fired (26 measures) and gas-fired power plants (11 measures).[56] These measures can be categorized into improvements for the boiler island, turbine island, flue gas system, air pollution controls and water treatment system, etc. We rank these measures by their unit cost, which yields marginal cost curves for heat rate reduction for coal-fired and gas-fired power plants, respectively (see Figure C1).

Figure C1. Marginal Cost of Heat Rate Reduction with All Measures

A. Marginal Cost of Heat Rate Reduction for Coal -fired Plants



B. Marginal Cost of Heat Rate Reduction for Gas -fired Plants



[56] The NDRC reports estimate the costs of these measures based on China's pilot energy conservation programs.

The estimation of the marginal cost curve presents a key challenge: it should exclude measures that have already been adopted, as it represents the costs of reducing heat rate from the cheapest measure. Following Burtraw et al. (2012), we assume that the observed heat rates are inversely correlated with the adoption of identified measures. Specifically, the power plants with higher emissions intensities have adopted fewer of the efficient techniques.

We first categorize all power plants according to their heat rates (see Table C1).[57] We consider the most inefficient group (highest heat rate) as having access to all heat rate reduction measures in Figure C2, resulting in a marginal cost curve identical to that in Figure C1. The most efficient group (lowest heat rate) is assumed to have only two measures with the two highest unit costs available, leading to its marginal cost curve matching the two far-right segments of Figure C2. For the groups that lie between these two extremes, we assume a linear relationship between their heat rate reduction potentials and their differences from the lowest heat rate group in terms of median heat rate. The resulting curves are in Figure C2.

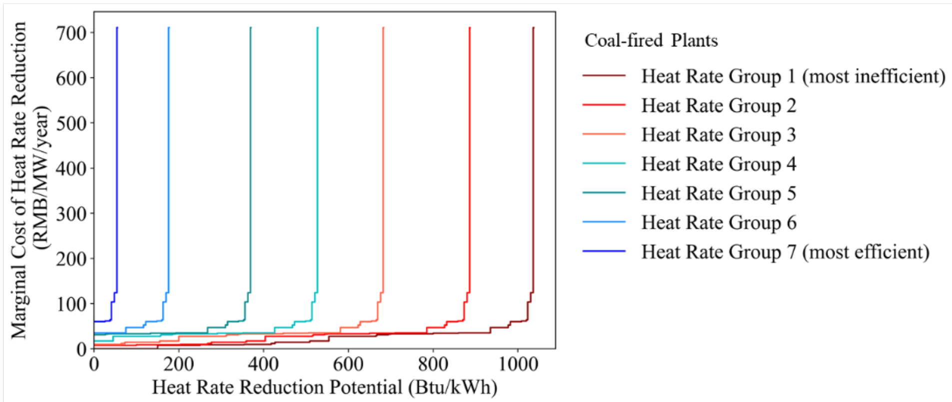
Table C1. Heat Rate Range by Heat Rate Groups

Heat rate group	Heat rate range (Btu/kWh)
Coal-Fired Power Plants	
1 (most inefficient)	(13,015/14,000)
2	(11,435/13,015)
3	(10,182/11,435)
4	(9,260/10,182)
5	(8,535/9,260)
6	(7,624, 8,535)
7 (most efficient)	(7,000/7,624)
Gas-Fired Power Plants	
1 (most inefficient)	(11,278/13,000)
2	(8,593/10,435)
3	(7,177/8,593)
4 (most efficient)	(6,000/7,177)

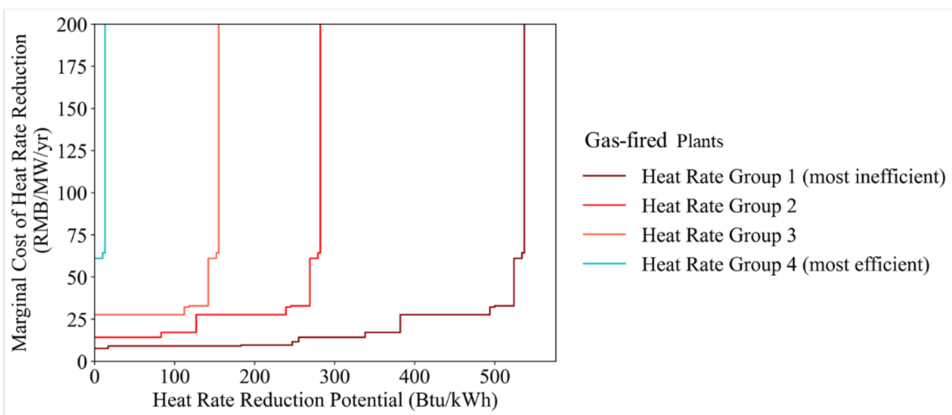
[57] We employ the k-means clustering algorithm to cluster all coal-fired power plants into seven groups with different heat rates and gas-fired power plants into four groups.

Figure C2. Marginal Cost of Heat Rate Reduction by Heat Rate Group

A. Marginal Cost of Heat Rate Reduction for Coal-fired Plants



B. Marginal Cost of Heat Rate Reduction for Gas-fired Plants



For each heat rate group, we then calibrate the price elasticity of the demand for fossil fuel input to fit the marginal cost curve (see Table C2). We calculate the elasticity in each subsector, considering the distribution of plants among the groups, as Equation A21 shows.

$$\varepsilon_k = \sum_h \vartheta_{kh} \varepsilon_h \ , \tag{A21}$$

where ε_k is the price elasticity of coal for subsector *k*, ε_h is the price elasticity of fossil fuel for heat rate group *h*, ϑ_{kh} is the output share of heat rate group *h* in subsector *k*. Finally, we use ε_k to calibrate the energy-factor elasticity in production, σ_{emw}, for each fossil-based electricity subsector.

Table C2. Calibrated Energy-Factor Elasticity of Substitution for Fossil-Based Electricity Subsectors

Fossil-Based Subsectors	Energy-Factor Elasticity of Substitution
Coal-Fired Subsectors	
LUSC	0.229
SUSC	0.219
LSC	0.259
SSC	0.253
LSUB	0.299
SSUB	0.295
LCFB	0.373
SCFB	0.340
OTHC	0.361
Gas-Fired Subsectors	
HPG	0.041
LPG	0.161

C.1.3. Parameters Related to Renewable Energy Supply

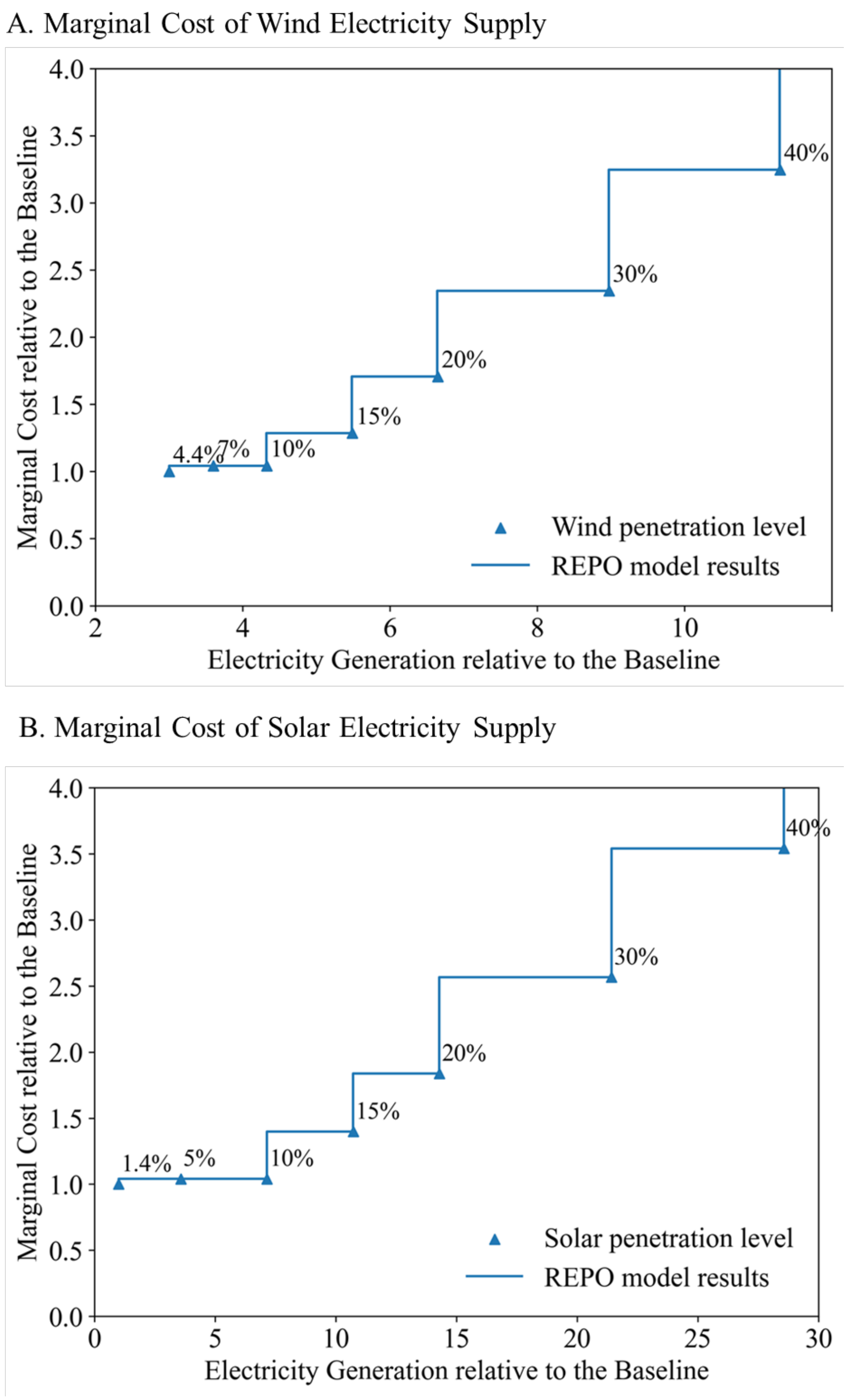
The calibration of the elasticity of substitution between the resource and other input, denoted as σ_{res}, and the share of natural resource input, θ_{res}, seeks to incorporate a detailed representation of renewable and nuclear electricity supply in China.

We use the Renewable Electricity Planning and Operation (REPO) Model[58] of China's power system, to acquire information on the marginal costs as a function of supply for

[58] This model (IEA and Tsinghua University, 2021; Zhang et al., 2023) captures China's power sector in great detail. The marginal cost is a combination of the marginal generation cost and the cost of integration. Generation costs depend on technology-specific investment and operation costs and site-specific wind and solar conditions. Integration costs include grid integration, balancing services, more flexible operation of thermal plants, and reserve costs and increase as the wind and solar penetration level rises (Hirth et al., 2015). The integration cost of wind or solar is complex and highly context specific. Therefore, the empirical studies, which focused on the United States and EU, may not be applicable to China, and we rely on REPO to derive the curves.

renewable and nuclear electricity, perform simulations of the model with different values of σ_{res} and θ_{res}, and identify the combinations that lead to similar marginal costs in the REPO model. The derived curves are shown in Figure C3.

Figure C3. Marginal Cost for Wind and Solar from the REPO Model



We use the following equation from the top-level next of the production function to calibrate the parameters σ_{res} and θ_{res} in that function.

$$Y = Y_0 \left(\frac{1-(1-\theta_{res}) \cdot (p/p_0)^{\sigma_{res}-1}}{\theta_{res}} \right)^{\frac{\sigma_{res}}{1-\sigma_{res}}} \tag{A22}$$

We obtain the values for σ_{res} and θ_{res} that best fit (using ordinary least squares) the supply curve in Figure C3.

For hydroelectricity and nuclear electricity, we use Leontief production functions, given that supplies of hydro and nuclear electricity in China are mainly constrained by planning and largely insensitive to electricity prices. Hence, for these subsectors, $\sigma_{res} = 0$. The θ_{res} parameter, representing the resource-related input not accounted for by other intermediate inputs or factor inputs, is derived from the literature. For hydroelectricity, it is calculated as the price difference between the hydroelectricity on-grid price (258.93 yuan/MWh) and the average on-grid electricity price (376.28 yuan/MWh) (NEA, 2018). The resulting θ_{res} is 0.3119 ($= \frac{376.28 - 258.93}{376.28}$). For nuclear electricity, θ_{res} equals 0.006 according to the share of payment for regional society in its total cost (IAEA, 2018).

C.1.4. Parameters Related to SOEs

As indicated in the main text and Appendix A, the model assumes two representative firms in each sector (or subsector, when subsectors are identified), with one each for SOEs and POEs. Table C3 presents for each sector the total output value and the SOE value share, based on data from the China Industrial Enterprise Database and China Input-Output Table.

Table C3. State-Owned Enterprises—Shares of Output

Sector	Benchmark-year output (trillion RMB)	SOE share (percent)
Cement	0.71	36
Iron and steel	5.89	36
Aluminum	0.72	31
Pulp and paper	1.92	8
Other nonmetal products	5.89	36
Other nonferrous metals	4.21	31
Raw chemicals	8.49	20
Agriculture	11.89	5
Mining	1.98	51
Food	13.22	23
Textile	4.04	3
Clothing	4.26	2
Log and furniture	2.66	6
Printing and stationery	2.39	8
Daily chemical products	7.06	8
Metal products	4.49	16
General equipment	8.26	19
Transport equipment	8.93	40
Electronic equipment	18.35	9
Other manufacturing	1.21	15
Water	0.26	53
Construction	23.02	39
Transport	14.97	77
Services	93.15	30

Electricity	4.88	87
Petroleum refining	5.77	69
Heat	0.60	87
Coal	2.34	69
Crude oil	0.81	92
Natural gas	0.37	46
Gas manufacture and distribution	0.43	46
Average	**2.62**	**31**

To achieve consistency with specific benchmark (2020) data, several conditions must be met. They are as follows. We express the conditions as they apply to subsectors. In the sectors without subsectors, they apply only at the sector level. Table C4 provides the definitions of symbols.

The coexistence of SOEs and POEs with outputs of the same type of good implies that their marginal costs of production are the same at the given market's output price, but their marginal cost curves exhibit different slopes. We calibrate the production functions of the SOEs and POEs so that the differing curves yield the same marginal cost at the benchmark levels of output. The differences in the slopes of the marginal cost curves are attributable in significant part to how the share of reproducible capital (an imperfectly mobile factor) varies at given output levels for the two firm types.

The calibration method is as follows. The parameter $\theta_{w_{jk}}$ denotes the observed benchmark share of reproducible capital inputs in marginal cost (see Table C4):

$$\theta_{w_{jk}} = \frac{w_{jk} p_{w_{jk}} (1 + \tau_{w_{jk}} - o_{w_{jk}})}{p_{jk} \overline{Y_{jk}}} . \qquad \text{(A23)}$$

We identify the values of w_{jk} consistent with equal marginal costs at the observed benchmark input and output levels. The equation systems denote the conditions.

The equal-marginal-cost condition is

$$\underbrace{\frac{w_{jk}{}^{S}}{\overline{Y_{jk}{}^{S}}}(1 - \overline{o_{wjk}{}^{S}}) + \frac{m_{jk}{}^{S}}{\overline{Y_{jk}{}^{S}}}(1 + \overline{\iota_{mjk}{}^{S}})}_{\text{marginal factor costs of SOEs}} = \underbrace{\frac{w_{jk}{}^{P}}{\overline{Y_{jk}{}^{P}}}(1 + \overline{\iota_{wjk}{}^{P}}) + \frac{m_{jk}{}^{P}}{\overline{Y_{jk}{}^{P}}}(1 + \overline{\iota_{mjk}{}^{P}})}_{\text{marginal factor costs of POEs}} . \qquad \text{(A24)}$$

(1) In each subsector, the ratio of SOE to POE capital intensities matches the observed level in the data.

$$\frac{w_{jk}^{S}}{Y_{jk}^{S}} / \frac{w_{jk}^{P}}{Y_{jk}^{P}} = \overline{B_j} \tag{A25}$$

(2) In each subsector, the combined capital used by SOEs and POEs matches the data.

$$w_{jk}^{S} + w_{jk}^{P} = \overline{w_{jk}} \tag{A26}$$

(3) In each subsector, the combined labor used by SOEs and POEs matches the data.

$$m_{jk}^{S} + m_{jk}^{P} = \overline{m_{jk}} \tag{A27}$$

(4) The combined tax revenue of SOEs and POEs, after deducting subsidies to each subsector, matches the data.

$$\overline{\iota_{wjk}^{P}} w_{jk}^{P} + \overline{\iota_{mjk}^{P}} m_{jk}^{P} + \iota_{mjk}^{S} m_{jk}^{S} - \overline{o_{wjk}^{S}} w_{jk}^{S} + \sum_{X} \overline{X_{jk}}\, \overline{\iota_{Xjk}} + \overline{Y_{jk}}\, \overline{\iota_{Yjk}} = \overline{T_{jk}} \tag{A28}$$

The five sets of conditions correspond to five types of parameters. For the cases where a subsector *k* applies, the five parameters are (a) w_{jk}^{S}, the benchmark capital input quantity of SOEs of sector *j*, subsector *k*; (b) w_{jk}^{P}, the benchmark capital input quantity of POEs of sector *j*, subsector *k*; (c) m_{jk}^{S}, the benchmark labor input quantity of SOEs of sector *j*, subsector *k*; (d) m_{jk}^{P}, the benchmark labor input quantity of POEs of sector *j*, subsector *k*; and (e) ι_{mjk}^{S}, the labor tax rate of SOEs of sector *j*, subsector *k*.

The relationship between parameters and conditions is not a simple one-to-one mapping, as some conditions (e.g., 1 and 5) are met by combinations of parameters. The conditions and parameters imply a *5jk* simultaneous equation system, which we solve by Gaussian Elimination.

Table C4. Parameters Related to State-Owned Enterprises

Symbol	Definition
j	Index for sector
k	Index for subsector
P	Superscript for POEs
S	Superscript for SOEs
$\overline{Y_{jk}}$	Total output quantity
$\theta_{w_{jk}}$	Benchmark share of capital input in marginal cost
$\overline{Y_{jk}^{S}}$	Output quantity of the SOEs
$\overline{Y_{jk}^{P}}$	Output quantity of the POEs
$\overline{X_{jk}}$	SOE and POE total quantity of intermediate inputs
$\overline{m_{jk}}$	SOE and POE total quantity of labor inputs
$\overline{w_{jk}}$	SOE and POE total quantity of capital inputs
w_{jk}^{S}	Quantity of SOEs' capital inputs
w_{jk}^{P}	Quantity of POEs' capital inputs
m_{jk}^{S}	Quantity of SOEs' labor inputs
m_{jk}^{P}	Quantity of POEs' labor inputs
$\overline{T_{jk}}$	Total taxes paid by SOEs and POEs
$\overline{\iota_{Xjk}}$	Tax rate of intermediate inputs
$\overline{\iota_{mjk}^{P}}$	Tax rate on POEs' labor inputs

ι_{mjk}^{S}	Tax rates on SOEs' labor inputs
$\overline{\iota_{wjk}^{P}}$	Tax rate on POEs' capital inputs
$\overline{o_{wjk}^{S}}$	Subsidy rate on SOEs' capital inputs
$\overline{\iota_{Yjk}}$	Tax rate per unit of output
$\overline{B_j}$	The ratio of capital input intensity of SOEs to that of POEs

Note: Symbols with bars represent the data or parameters observed or obtained from other studies. Symbols without bars are the parameters that require calibration.

C.1.5. Other Parameters

Other elasticities are adopted from the GTAP database (Aguiar et al., 2019), MIT-EPPA model (Chen et al., 2017), RTI-ADAGE model (RTI International, 2015), DIEM model (Ross, 2014), and literature (Cossa, 2004; Hertel et al., 2007; Hertel and Mensbrugghe, 2019; Jomini et al., 1991; Lian et al., 2020). Table C5 lists the values for these parameters.

Table C5. Elasticities

Parameter	Source	Values
Production elasticities		
σ_{res}	Calibrated	Solar: 0.27 Wind: 0.28 Hydro, Nuclear: 0
σ_{xemw}	GTAP, EPPA, RTI-ADAGE, DIEM	0
σ_{emw}	Calibrated	Electricity: 0.04 - 0.37 (see Table C2) Other sectors: 0.4
σ_{e}	Calibrated	Other sectors: 0.50; Electricity: 0.01
σ_{h}	Hu et al. (2019)	0.30
σ_{f}	Cossa (2004), RTI-ADAGE	Other sectors: 1.00; Electricity: 0.10
σ_{mw}	Jomini et al. (1991)	Agriculture: 0.24 Coal, Crude oil, Natural gas, Mining: 0.20 Food: 1.12 Services: 1.36 Transportation: 1.48 Other sectors: 1.26
σ_{x}	GTAP, EPPA, DIEM	0
σ_{n}	Hertel et al. (2007)	Mining: 1.80 Construction, Transportation, Services: 3.80 Petroleum refining: 4.20 Agriculture: 4.84 Food: 5.09 Cement, Other nonmetal products: 5.80 Water, Gas manufacture and distribution, Electricity, Heat: 5.60 Pulp and paper, Iron and steel, Printing and stationery: 5.90 Coal: 6.10 Transport equipment: 6.31 Raw chemicals, Daily chemical products: 6.60 Log and furniture: 6.80 Textile, Metal products, Other manufacturing: 7.50 Clothing: 7.63 General equipment: 8.10 Aluminum, Other nonferrous metals: 8.40 Electronic equipment: 8.80 Crude oil: 10.40

		Natural gas: 16.00
$\boldsymbol{\sigma_{ds}}$	GTAP	Same as σ_n
Consumption elasticities		
$\boldsymbol{\sigma_{xs}}$	GTAP	0
$\boldsymbol{\sigma_s}$	Calibrated	0.55
$\boldsymbol{\sigma_f}$	DIEM	0.50
$\boldsymbol{\sigma_x}$	GTAP	Household consumption: 1.00
		Government consumption, investment: 0
Saving elasticity		
$\boldsymbol{\sigma_{CS}}$	Calibrated	1.50
Transformation elasticities*		
$\boldsymbol{\sigma_{\mathrm{w}}}$	GTAP	1.50 for capital, +∞ for labor
$\boldsymbol{\sigma_{w_k}}$	GTAP	3.00 for capital, +∞ for labor
$\boldsymbol{\sigma_{w_{k\_sp}}}$	GTAP	6.00 for capital, +∞ for labor

* σ_w, σ_{w_k}, and $\sigma_{w_{k\_sp}}$ represent the factor transformation elasticities between sectors, subsectors within a sector, and state-owned and private-owned enterprises within a subsector, respectively.

C.2. Parameters Influencing Intertemporal Allocation and Dynamics

Other parameters are closely related to intertemporal choices and economic growth. These include the growth rate of effective labor, rate of autonomous energy efficiency improvement, savings rate, reproducible capital depreciation rate, and interest rate.

Capital growth stems from private and public savings. According to Zhang et al. (2018), China's public saving has been around 3 percent of GDP in recent years. Using this data along with total investment data from the China IO table, we calculate private and public savings for the base year (2020). Then the two saving rates are determined to ensure that the resulting public and private savings match the base-year data. The private saving rates for subsequent years are determined by Equation A17. In the central case, we apply a private saving rate annual reduction factor of 0.6 percent. This yields a baseline path for private saving rates consistent with the projected declining trends in China's saving rates, according to Zhang et al. (2018). The public saving rate is assumed to remain constant at 3 percent of GDP, following Zhang et al. (2018).

Real investment level in each period *t* is determined by total savings and the unit price of investment goods in that period. Capital growth from period *t* to *t*+1 is calculated as the investment of period *t* net of depreciation during period *t*. We apply an annual depreciation rate of 5 percent, following Herd (2020). The initial capital stock for the base year (2020) is derived from Holz and Sun (2018).

Technological progress takes two forms: autonomous energy efficiency improvement (AEEI) and Hicks-neutral technological change. For sectors excluding the fossil-based electricity sector, we follow Chen et al. (2017), applying a 1 percent annual AEEI rate. For the fossil subsectors, we again follow Chen et al. (2017), applying an annual AEEI rate of 0.4 percent.

Hicks-neutral technological change applies to all sectors but at different rates across sectors. These differences give rise to important structural changes in China—in particular, the transition involving increased representation of the service sector (Święcki, 2017) and the increased penetration of renewable electricity. The rates of Hicks-neutral technological changes are set so that the model's baseline path is consistent with the projections by the State Information Center (2020) and IRENA (2019). In keeping with these requirements, in the baseline, the GDP contributions from agriculture, industry, and service sectors are projected to change from 7, 37, and 56 percent to 6, 30, and 64 percent, respectively, for 2020–2035; wind and solar energy costs decline by 36 percent over this interval.

C.3. Value of Benchmarks

Table C6 shows the TPS benchmarks for each sector in different cases.

Table C6. Initial Benchmarks

Sectors and Subsectors	Policy Cases					
	Case 1	Case 2a	Case 2b	Case 3a	Case 3b	Case 3c
Electricity (tCO_2/MWh):						
Coal-fired generators with capacity <300 MW (SSC, SSUB, and OTHC)	0.882	0.859	0.833	0.882	0.882	0.882
Coal-fired generators with capacity >= 300 MW (LUSC, SUSC, LSC, and LSUB)	0.824	0.859	0.833	0.824	0.824	0.824
Circulating fluidized bed generators (LCFB, SCFB)	0.940	0.859	0.833	0.940	0.940	0.940
Gas-fired generators (HPG, LPG)	0.394	0.393	0.833	0.394	0.394	0.394
Cement (tCO_2/ton)	0.849	0.848	0.848	0.849	0.849	0.849
Iron and steel (tCO_2/ton):						
Basic oxygen furnace	0.017	0.017	0.017	0.017	0.017	0.017
Electric arc furnace	0.004	0.004	0.004	0.004	0.004	0.004
Aluminum (tCO_2/ton)	7.911	7.910	7.905	7.911	7.911	7.911
Other nonmetal products (tCO_2/*k*RMB)	0.058	0.058	0.058	0.057	0.057	0.057
Other nonferrous metals (tCO_2/*k*RMB)	0.051	0.051	0.051	0.050	0.050	0.050
Pulp and paper (tCO_2/*k*RMB)	0.050	0.050	0.050	0.049	0.049	0.049
Petroleum refining (tCO_2/*k*RMB)	0.039	0.039	0.039	0.038	0.038	0.038
Raw chemicals (tCO_2/*k*RMB)	0.092	0.091	0.091	0.090	0.089	0.089

Note. "Initial benchmarks" refers to the values when they are first introduced under the TPS. For the electricity sector, the benchmarks first apply in 2020. For sectors first introduced in Phase 2, they first apply in 2023. For the sectors first introduced in Phase 3, they first apply in 2026.

Appendix D. The Significance of Pre-Existing Taxes

To confirm the impacts of pre-existing taxes on the relative cost of the TPS and C&T, we performed counterfactual simulations altering the tax rates on capital, labor, and intermediate inputs. As indicated in Table D1, the cost ratio of TPS to C&T reduces as the magnitude of pre-existing taxes increases.

Table D1. Cost Ratio of TPS to C&T Under Different Assumptions of the Extent of Pre-Existing Taxes in 2020–2035

Scale of Pre-Existing Taxes*	TPS/C&T Cost Ratio
0.0	1.112
0.5	1.104
1.0	1.097
1.5	1.084
2.0	1.073

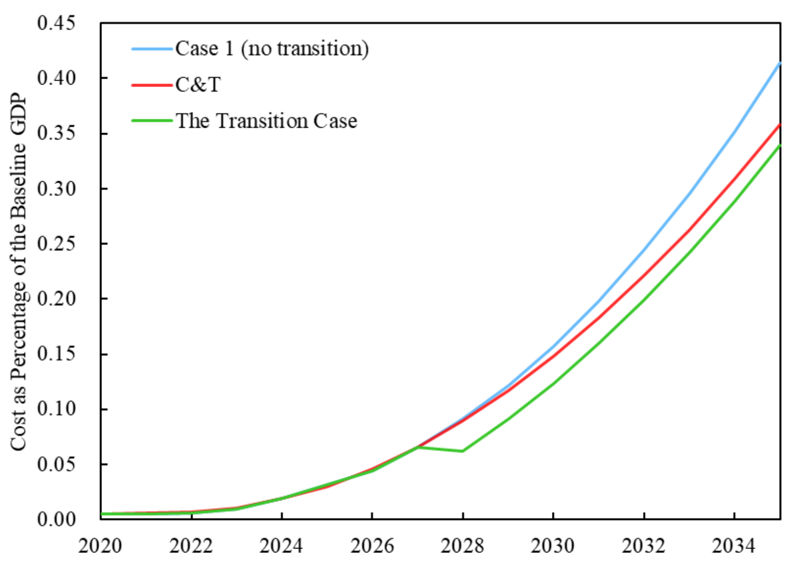
*The scale is the magnitude of pre-existing tax rates relative to the rates in the central case.

Appendix E. Dynamics of a Potential Transition from a TPS to a C&T

In Section 6.1.2, we compared the costs of the TPS and an equally stringent C&T system when each policy was introduced in 2020 and maintained over the entire simulation period. In this appendix, we consider a scenario in which the TPS transitions to a C&T at some future time, which China's planners are considering; the system is a TPS before 2028 and a C&T after 2028. That is, the transition is completed in one year, and the two never coexist.[59]

Figure E1 shows the costs of Case 1, C&T, and the transition case. The transition case has lower costs than the other two since 2028. Its economic cost is lower than the TPS because of the absence of the implicit output subsidy and lower than C&T because of the differences in capital accumulation before the transition. Before the transition year, when the TPS applies in the transition case, the aggregate investment is higher than in the C&T case. The higher investment reflects TPS's implicit output subsidy, which implies lower prices of the more emission-intensive capital goods. As a result, during and after the transition, the economy's capital endowment in the transition case is higher than in C&T, implying a lower rental price of capital, which implies a lower cost of CO_2 abatement, as covered facilities can switch at a lower cost from carbon-based fuels to capital in production.

Figure E1. Economic Cost Under Transition to a Full C&T System, 2020–2035



[59] In an alternative scenario, we assume the transition is gradual, starting in 2028 and completed by 2030. The TPS and C&T are both in place in 2028 and 2029, and C&T is the only system starting in 2030. During the transition period, the free allowances allocated by TPS's benchmarks account for 2/3 and 1/3 of those in 2028 and 2029. This scenario yields results similar to those in the immediate transition case.

Appendix F. Evaluation of $PM_{2.5}$ Concentrations and Corresponding Health Cobenefits

For the health cobenefits from avoided premature deaths, we apply an emission inventory model (described in Zheng et al. 2019), an air-quality model (Polynomial function-based Response Surface Model (Pf-RSM) described in Xing et al. 2018), and the Global Exposure Mortality Model (GEMM) developed by Burnett et al. (2018) to calculate $PM_{2.5}$-related premature mortalities under the baseline and the TPS.

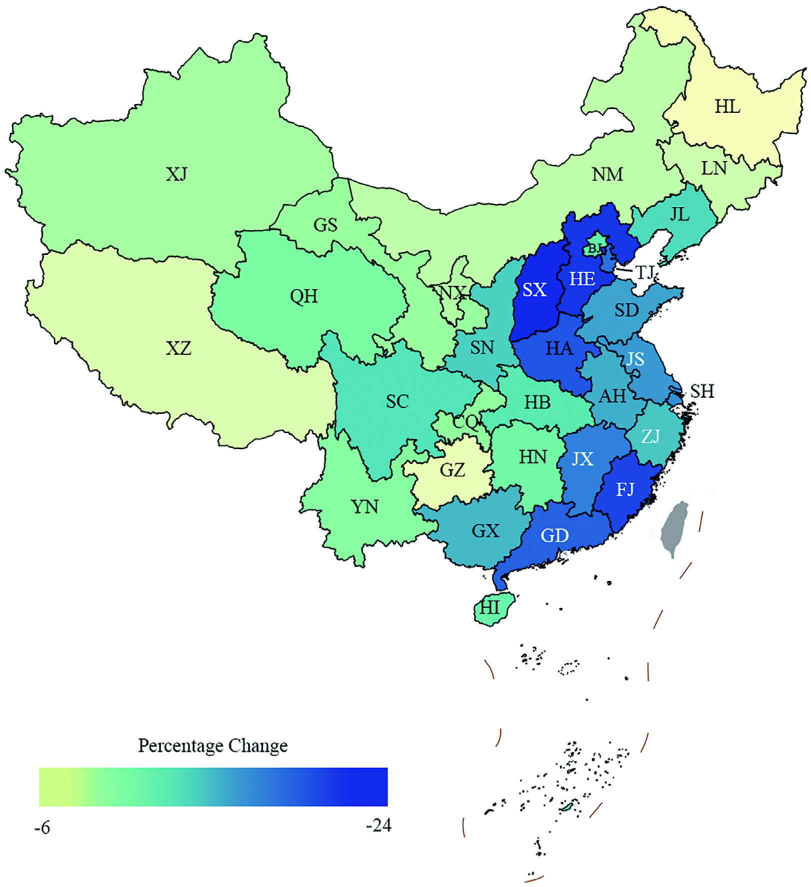
The emissions inventory model is the Air Benefit and Cost and Attainment Assessment System—Emission Inventory (ABaCAS-EI), which was jointly developed by the School of Environment at Tsinghua University, the Southern China University of Technology, and the University of Tennessee. It is widely used in China's air-quality research. It covers six major categories of anthropogenic emissions sources, each of which is further divided top down into industry-level, fuel-level, and technology-level subsectors.

The air-quality model is the Pf-RSM, which was developed by the School of Environment. It combines mathematical and statistical methods and performs stable emissions concentration-response simulation.

To link the dynamic general equilibrium model to the air-quality model, we run the former model to obtain results for sectoral fuel consumption and sectoral outputs. We multiply these results by the energy emission factors in the ABaCAS-EI emissions inventory to yield sectoral pollutant emissions at the provincial level.[60] The air pollutants we consider include SO_2, NOx, NH_3, nonmethane volatile organic compounds, and primary particulate matter. The provincial sectoral emissions serve as inputs to the RSM model, which simulates the local air pollution concentrations for each province for each year. We focus on changes in provincial $PM_{2.5}$ concentration because studies suggest that $PM_{2.5}$ is and will continue to be responsible for a large fraction of premature mortality from air pollution in the next several decades (Burnett et al., 2018; Zhou et al., 2019; Wang et al., 2021). Figure F1 represents the results for 2035. Similar patterns appear in other years, differing only in magnitude.

[60] We assume that for 2020–2035, the spatial distribution of firms within an industry and energy emission factors do not change.

Figure F1. Changes in $PM_{2.5}$ Concentrations Under the TPS Relative to the Baseline, 2035



Note: The abbreviations for provinces are AH: Anhui, BJ: Beijing, CQ: Chongqing, FJ: Fujian, GS: Gansu, GD: Guangdong, GX: Guangxi, GZ: Guizhou, HI: Hainan, HE: Hebei, HL: Heilongjiang, HA: Henan, HB: Hubei, HN: Hunan, JS: Jiangsu, JX: Jiangxi, JL: Jilin, LN: Liaoning, NM: Inner Mongolia, NX: Ningxia, QH: Qinghai, SN: Shaanxi, SD: Shandong, SH: Shanghai, SX: Shanxi, SC: Sichuan, TJ: Tianjin, XJ: Xinjiang, XZ: Tibet, YN: Yunnan, and ZJ: Zhejiang. Results for Hong Kong, Macao, and Taiwan are not included due to data limitations in their emissions inventories.

We calculate the health-related benefits from reduced air pollution concentrations as follows. First, we apply the GEMM NCD+LRI method (Burnett et al., 2018) to estimate avoided premature death related to reductions in chronic exposure to outdoor $PM_{2.5}$ under different scenarios. GEMM NCD+LRI adopts the following equation to quantify the relationship between the hazard ratio (RR) and ambient $PM_{2.5}$ concentration (c):

$$RR(c) = \exp\left(\theta \times \frac{\ln\left(\frac{\max(0, c - c_f)}{\alpha} + 1\right)}{1 + \exp\left(-\frac{\max(0, c - c_f) - \mu}{\nu}\right)}\right), \tag{A29}$$

where θ, α, μ, ν, and c_f are shape parameters and are adopted from Burnett et al. (2018). Avoided deaths can then be calculated using Equation A30.

$$\Delta M_t = \sum_{m,p} M_m^B \times pop_{p,t} \times \left(\frac{1}{RR(c_{TPS,t})} - \frac{1}{RR(c_{BS,t})}\right), \tag{A30}$$

where $c_{BS,t}$ is the $PM_{2.5}$ concentration under the baseline in period t, and $c_{TPS,t}$ is the $PM_{2.5}$ concentration under the TPS in period *t*. M_m^B are the mortality rates with the lowest level of exposure to $PM_{2.5}$ for age group *m* in China and retrieved from the Global Health Data Exchange. We follow the convention to divide the national population into 12 subgroups (adults aged 25–85+ in five-year intervals); pop_p^t are the baseline provincial population projections in period *t* and sourced from Chen et al. (2020).

We consider the uncertainties related to the hazard ratio from equation A29. Following Burnett et al. (2014), we assume that θ has a normal distribution, sample 1,000 points from it, and calculate the mean and 95 percent confidence interval (CI) of avoided death, using Equation A30 (see Table F1); the CI for 2020–2035 is 2.3–2.5 million, and the interval for the average number of deaths annually is 142,000–159,000.

Table F1. Average Annual Avoided Deaths Under the TPS, 2020–2035 (thousands)

Provinces	Annual avoided deaths	95% confidence interval
Beijing	2.3	(2.2–2.4)
Tianjin	2.1	(2–2.2)
Hebei	10.7	(10.2–11.2)
Shanxi	5.3	(5–5.6)
Inner Mongolia	1.6	(1.5–1.7)
Liaoning	5.0	(4.8–5.3)
Jilin	1.9	(1.8–2)

Heilongjiang	1.0	(0.9–1)
Shanghai	2.9	(2.8–3.1)
Jiangsu	10.0	(9.4–10.5)
Zhejiang	5.9	(5.6–6.3)
Anhui	7.2	(6.7–7.6)
Fujian	3.8	(3.6–4.1)
Jiangxi	5.5	(5.1–5.8)
Shandong	13.0	(12.3–13.6)
Henan	15.0	(14.2–15.8)
Hubei	7.0	(6.6–7.4)
Hunan	6.8	(6.4–7.1)
Guangdong	11.8	(11.1–12.6)
Guangxi	5.7	(5.4–6)
Hainan	0.6	(0.6–0.7)
Chongqing	2.5	(2.3–2.6)
Sichuan	7.8	(7.4–8.3)
Guizhou	2.1	(2–2.2)
Yunnan	3.3	(3.1–3.6)
Tibet	0.1	(0.1–0.1)
Shaanxi	4.2	(4–4.5)
Gansu	2.0	(1.9–2.1)
Qinghai	0.5	(0.5–0.6)
Ningxia	0.5	(0.5–0.5)
Xinjiang	2.3	(2.1–2.4)

Note: Hong Kong, Macao, and Taiwan are not included due to data limitations in their emissions inventories.

Appendix G. Estimation of the Geographical Cost Distribution

To assess the geographical distributional impacts, we use the following method. Let INC_{ikp} be the income of sector *i* subsector *k* in province *p*, and INC_p be the income of all sectors in province *p*.

$$INC_p = \sum_{ik} INC_{ik} \frac{INC_{ikp}}{INC_{ik}} \tag{A31}$$

In Equation A31, $\frac{INC_{ikp}}{INC_{ik}}$ represents the share of the income from sector *i* subsector *k* in province *p* in the national income from sector *i* subsector *k*. We assume these shares are the same and remain at the base year's level for all years and in all scenarios. $\frac{INC_{ikp}}{INC_{ik}}$ in the base year can be calculated from the provincial input-output tables and the firm-level MEE data (see Section 4.1).

Let ΔINC_p be the change of income of province *p*, then

$$\Delta INC_p = \sum_{ik} \Delta INC_{ik} \frac{INC_{ikp}}{INC_{ik}} . \tag{A32}$$

Equation A32 is used to calculate the absolute change of the provincial income presented in Table G1. The percentage change can then be calculated by $\frac{\Delta INC_p}{INC_p}$.

Table G1. Cumulative Income Change by Province, 2020–2035

Provinces	Four-Benchmark (Case 1)		Two-Benchmark (Case 2a)		One-Benchmark (Case 2b)	
	Absolute Change (billion RMB)	Percent Change (%)	Absolute Change (billion RMB)	Percent Change (%)	Absolute Change (billion RMB)	Percent Change (%)
East						
Hebei	44	0.062	-46	-0.065	-202	-0.275
Shandong	-229	-0.154	-287	-0.193	-704	-0.458
Liaoning	-30	-0.061	-28	-0.056	-139	-0.270
Jiangsu	-96	-0.055	-92	-0.053	622	0.346
Hainan	-11	-0.119	-19	-0.195	-19	-0.197
Zhejiang	-47	-0.045	-3	-0.003	79	0.073
Fujian	14	0.022	61	0.092	133	0.195
Shanghai	-104	-0.162	-56	-0.086	74	0.111
Guangdong	-210	-0.115	-205	-0.111	573	0.301
Tianjin	-40	-0.109	-20	-0.055	214	0.566
Beijing	-123	-0.193	-122	-0.190	214	0.323
Regional Total	-833	-0.086	-817	-0.084	844	0.084
Central						
Shanxi	-298	-0.889	-393	-1.169	-420	-1.208
Heilongjiang	-158	-0.453	-175	-0.498	-193	-0.534
Henan	-74	-0.079	-64	-0.068	-156	-0.161
Anhui	-83	-0.144	51	0.089	-197	-0.332
Jilin	-35	-0.121	-30	-0.102	-26	-0.086
Hubei	14	0.018	1	0.001	-53	-0.068
Hunan	-51	-0.074	-34	-0.048	-18	-0.025
Jiangxi	38	0.096	76	0.189	18	0.043

Inner Mongolia	-155	-0.487	-150	-0.470	-586	-1.771
Regional Total	-802	-0.173	-718	-0.154	-1631	-0.339
			West			
Ningxia	54	0.790	21	0.298	-70	-0.986
Guizhou	-133	-0.492	-114	-0.422	-217	-0.775
Shaanxi	-222	-0.490	-249	-0.547	-114	-0.243
Yunnan	15	0.043	-7	-0.021	-66	-0.187
Guangxi	8	0.020	24	0.061	-38	-0.094
Xinjiang	16	0.059	17	0.064	-17	-0.063
Chongqing	-57	-0.141	-41	-0.101	-38	-0.092
Gansu	-14	-0.083	-45	-0.269	-112	-0.642
Sichuan	-85	-0.103	-69	-0.084	82	0.097
Qinghai	34	0.587	41	0.690	41	0.667
Regional Total	-384	-0.119	-423	-0.130	-550	-0.164
National	-2019	-0.115	-1958	-0.111	-1338	-0.073
Standard deviation		0.297		0.307		0.502

Note: The red font identifies the five provinces with the largest percentage income losses in a given benchmark case; the green font identifies the five with the smallest percentage losses (or largest percentage increases). Hong Kong, Macao, Tibet, and Taiwan are not included due to input-output data limitations.

Appendix H. Sensitivity Analysis

We examine the sensitivity of the model's results to input substitution elasticities, capital transformation elasticities, the parameters that determine the model's dynamics, and the assumed rates of increase in policy stringency.

Table H1 shows the significance of input substitution and transformation elasticities. A higher elasticity of substitution between energy and other inputs lowers the cost of reducing emissions intensities by substituting material inputs for high-carbon fuels. Similarly, a higher capital transformation elasticity implies lower costs of reallocating capital from the low-efficiency to high-efficiency subsectors in response to a changing policy environment. Thus, costs per ton decline with a higher value for this elasticity.

Table H2 focuses on parameters that directly influence the dynamics. The AEEI rate is the growth rate of exogenous energy-factor productivity in production; a higher rate implies faster growth of energy efficiency and lower baseline emissions, meaning that the economic costs per ton decline.

The elasticity of substitution between household consumption and private saving determines the responsiveness of saving to changes in the return to capital. Under the TPS, the price of investment goods increases relative to that of consumption goods, reflecting the greater emissions intensity of investment goods. This change leads to a lower saving rate and rate of capital accumulation relative to the baseline. A higher elasticity amplifies this effect. Greater capital accumulation facilitates firms in substituting carbon-intensive inputs with capital inputs. Therefore, in cases with a higher (lower) elasticity between consumption and saving, the TPS incurs a slightly higher (lower) cost per ton compared to the central case.

Table H3 examines the significance of assumptions about future policy stringency, as determined by the rate of benchmark tightening after 2022. In the central case, benchmarks are tightened by 1.5 and 2.5 percent annually for the electricity and nonelectricity sectors, respectively. We consider two alternative scenarios. In the low (high) stringency scenario, electricity sector benchmarks are tightened by 1 (2) percent annually and nonelectricity sectors' benchmarks by 2 (3) percent. The cumulative emissions reductions in the high-stringency case are approximately 29 percent higher than in the central case. Costs per ton of abatement increase with the level of stringency, reflecting rising marginal costs of abatement.

The bottom row in Tables H1, H2, and H3 indicates how the ratio of the TPS's costs to those under C&T depends on key parameters. As discussed in Section 2, the TPS's implicit output subsidy is the product of the allowance price and the applicable benchmark. Thus a lower carbon price implies a smaller subsidy and associated distortion under the TPS. A higher energy-factor substitution elasticity, higher AEEI rate, and lower benchmark tightening rate all work to lower allowance prices by implying lower costs of reducing emissions and lower demands for allowances, leading to a lower ratio of TPS to C&T costs.

In contrast, the influence of capital transformation elasticity on the ratio of TPS costs to C&T is ambiguous. It depends on differences in how much the two policies rely on changes in sector composition to reduce emissions.[61] The relative reliance changes over time. The TPS relies more in Phase 1, and C&T relies more in Phases 2 and 3,[62] so easier capital transformation would benefit the TPS more in the first few years and C&T more after that.

Overall, our main findings on the impacts of the TPS are robust to changes in these parameters. This includes the findings that the TPS's environmental benefits significantly exceed its economic costs, planned stringency is less than the efficiency-maximizing level, and costs become higher than those of an equivalently stringent C&T system once the system reaches a critical level of stringency.[63]

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[61] As indicated in Subsection 6.1.2, shifts in sectoral composition provide one of three main channels through which the TPS can yield reduced economywide emissions, with the others being reduced output supply and reduced emissions intensity at the firm level.

[62] In Phase 1, under the TPS and C&T, the contributions from changes in sector composition to emission reductions are 54 and 47 percent, respectively. The two policies' reliance on change in sector composition is 31 and 39 percent in Phase 2 and 25 and 38 percent in Phase 3.

[63] The bottom set of rows in tables H1, H2, and H3 shows that the TPS can involve lower costs than C&T in certain cases: (a) the energy-factor substitution elasticities are twice those of the central case, (b) the AEEI rate is high (1.5 percent), or (c) the benchmark tightening rate is modest. Under both the TPS and C&T, these alternative specifications lower marginal abatement costs compared to the central case. But the cost reduction is higher for the TPS because these changes reduce the distortionary effects of its implicit output subsidy. In the central case, the TPS's cost-disadvantage is relatively small because the subsidy reduces the adverse tax-interaction effect described in Subsection 6.1.2. In these three cases, the reduction in the TPS's costs is large enough to bring them below those of C&T.

Table H1. Sensitivity Analysis: Significance of Production and Capital Transformation Elasticities

	Central Case	Energy-Factor Substitution Elasticity				Capital Transformation Elasticity	
		of All Sectors		of the ELEC Sector			
		Halved	Doubled	Halved	Doubled	Halved	Doubled
Emission reduction (billion tons):							
Phase 1 (2020–2022)	0.41	0.38	0.45	0.39	0.43	0.42	0.40
Phase 2 (2023–2025)	1.32	1.25	1.45	1.28	1.40	1.32	1.33
Phase 3 (2026–2035)	19.08	18.30	20.89	19.09	19.35	19.08	19.13
Present value of cost (billion RMB):							
Phase 1 (2020–2022)	17	19	16	19	15	20	14
Phase 2 (2023–2025)	63	70	59	66	60	68	57
Phase 3 (2026–2035)	1,939	2,451	1,593	2,076	1,727	2,064	1,776
Economic cost per ton (RMB/ton):							
Phase 1 (2020–2022)	41	49	35	49	34	47	34
Phase 2 (2023–2025)	48	56	40	51	42	51	43
Phase 3 (2026–2025)	102	134	76	109	89	108	93
Allowance price (RMB/ton):							
Phase 1 (2020–2022)	61	84	41	84	41	74	47
Phase 2 (2023–2025)	88	120	61	98	75	98	76
Phase 3 (2026–2025)	408	636	244	454	335	445	357
Wind and solar increase (%):							
Phase 1 (2020–2022)	0.30	0.31	0.28	0.31	0.28	0.43	0.18
Phase 2 (2023–2025)	0.70	0.93	0.50	0.75	0.65	0.84	0.53
Phase 3 (2026–2025)	5.63	8.70	3.34	6.81	4.14	5.94	4.88

Ratio of TPS to C&T cost:							
Phase 1 (2020–2022)	0.97	1.19	0.80	1.12	0.86	1.01	0.93
Phase 2 (2023–2025)	1.03	1.18	0.91	1.08	0.97	1.00	1.07
Phase 3 (2026–2025)	1.10	1.29	0.98	1.14	1.03	1.05	1.19

Note: The words "halved" and "doubled" indicate how the parameters in the sensitivity analysis are changed relative to their value in the central case.

Table H2. Sensitivity Analysis: Significance of Key Dynamic Parameters

	Annual AEEI Rate (percent)			Elasticity Between Private Saving and Consumption		
	0.5	**1**	**1.5**	**1**	**1.5**	**2**
		(Central case)		**(Constant saving rate)**	**(Central case)**	
Cumulative emissions reduction (billion tons):						
Phase 1 (2020–2022)	0.41	0.41	0.41	0.41	0.41	0.41
Phase 2 (2023–2025)	1.39	1.32	1.26	1.32	1.32	1.33
Phase 3 (2026–2035)	21.31	19.1	16.9	18.99	19.08	19.17
Present value of cumulative cost (billion RMB):						
Phase 1 (2020–2022)	17	17	17	17	17	17
Phase 2 (2023–2025)	69	63	57	63	63	63
Phase 3 (2026–2035)	2,475	1,939	1,495	1,884	1,939	1,992
Economic cost per ton (RMB/ton)						
Phase 1 (2020–2022)	41	41	41	41	41	41
Phase 2 (2023–2025)	50	48	45	47	48	48
Phase 3 (2026–2035)	116	102	89	99	102	104

Average allowance price (RMB/ton):						
Phase 1 (2020–2022)	61	61	61	61	61	61
Phase 2 (2023–2025)	94	88	83	88	88	88
Phase 3 (2026–2035)	496	408	330	407	408	408
Wind and solar electricity increase (%):						
Phase 1 (2020–2022)	0.29	0.30	0.31	0.30	0.30	0.30
Phase 2 (2023–2025)	0.69	0.70	0.71	0.70	0.70	0.70
Phase 3 (2026–2035)	5.76	5.63	5.34	5.63	5.63	5.63
Ratio of TPS cost to C&T cost:						
Phase 1 (2020–2022)	0.97	0.97	0.97	0.98	0.97	0.96
Phase 2 (2023–2025)	1.08	1.03	0.98	1.07	1.03	1.00
Phase 3 (2026–2035)	1.24	1.10	0.99	1.19	1.10	1.03

Note: The words “halved” and “doubled” indicate how the parameters in the sensitivity analysis are changed relative to their value in the central case.

Table H3. Sensitivity Analysis: Significance of Policy Stringency

	Benchmark Annual Tightening Rate		
	Low[a]	**Central[b]**	**High[c]**
Cumulative emissions reduction (billion tons)			
Phase 1 (2020–2022)	0.41	0.41	0.41
Phase 2 (2023–2025)	1.08	1.32	1.57
Phase 3 (2026–2035)	13.62	19.08	24.93
Present value of cumulative cost (billion RMB)			
Phase 1 (2020–2022)	17	17	17
Phase 2 (2023–2025)	45	63	85
Phase 3 (2026–2035)	1,032	1,939	3,203

Economic cost per ton (RMB/ton)			
Phase 1 (2020–2022)	41.2	41.2	41.2
Phase 2 (2023–2025)	41.7	47.6	53.9
Phase 3 (2026–2035)	75.8	101.6	128.5
Average allowance price (RMB/ton)			
Phase 1 (2020–2022)	61	61	61
Phase 2 (2023–2025)	68	88	111
Phase 3 (2026–2035)	242	408	629
Wind- and solar- electricity increase (%)			
Phase 1 (2020–2022)	0.30	0.30	0.30
Phase 2 (2023–2025)	0.42	0.70	1.08
Phase 3 (2026–2035)	2.00	5.63	11.56
Ratio of TPS cost to C&T cost			
Phase 1 (2020–2022)	0.97	0.97	0.97
Phase 2 (2023–2025)	0.91	1.03	1.13
Phase 3 (2026–2035)	0.92	1.10	1.23

[a] 1 percent for electricity; 2 percent for other sectors.
[b] 1.5 percent for electricity; 2.5 percent for other sectors.
[c] 2 percent for electricity; 3 percent for other sectors.

Appendix References

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